SIGNALING AND SEARCH IN HUMANITARIAN GIVING: MODELS OF DONOR AND ORGANIZATION BEHAVIOR IN THE HUMANITARIAN SPACE

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SIGNALING AND SEARCH IN HUMANITARIAN GIVING: MODELS OF DONOR AND ORGANIZATION BEHAVIOR IN THE HUMANITARIAN SPACE

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To my grandmother,

Grace E. Willis,

whose example and support made this possible.

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SUMMARY

As of 2006, the amount of private contributions to US based 501(c)(3) nonprofit charities totaled around $295 billion, representing an almost 28% increase over the same figure in the year 2000. Coupled with an almost 35% increase in the number of charities between 1995 and 2005, from 572,660 to 876,164, a picture begins to emerge of a rapidly growing sector, with both increased market size and increased competition. While the increased funding is beneficial to the sector at large, whether or not increased competition is beneficial remains an open question. One of the side effects of the growth explosion, particularly from the donor perspective, is increasing complexity in the decision process. Furthermore, when one considers that donors often times contribute to charitable goods of which they do not directly benefit, the question of how one ascertains the quality of such goods adds a layer of complexity to the decision problem. At its core, this dissertation examines the role of information, particularly as it relates to proxies for quality, and how it affects both the donor and organization decision processes in the humanitarian space.

In Chapter 2 I consider the context of competition within the sub-sector of international humanitarian relief organizations. It has been observed that large scale humanitarian relief events tend to spawn highly competitive environments in which organizations compete with one another for publicity and funding, often times to the detriment of effective resource utilization. The question of why altruistic organizations behave in this manner arises. Positing that competition is a result of dual organization objectives and the inability to credibly signal quality a model of signaling is presented to explain this phenomenon, and conditions under which pooling and

separating equilibrium can occur are shown. Results are shown to match closely with observed behavior, and potential policy remedies are considered using the model as a foundation.

Chapter 3 addresses a similar question but broadens the analysis to that of a general market for charitable goods. Building on foundational results in search theory, I propose a two-stage model of donor search behavior to explain the effects of transparency and exposure on both donor and organization behavior as it regards how donors select organizations. Using both analytical and simulated results I show how donor behavior changes under various market constructions, with implications on total market outcomes and organization behavior discussed.

Chapter 4 concludes with an empirical analysis to test the assumptions and results from the models of Chapters 2 and 3. Using an observational data set provided by the online charitable giving marketplace GlobalGiving, fixed effects panel regression and logit models are used to investigate the effects of transparency on both the amount of a donor's gift, and on the likelihood of repeat giving. Results are complicated by discussed validity issues, and in general show that within the context of GlobalGiving proxied transparency does not appear to have a significant practical effect on either the amount of the gift or organization selection by a given donor. While some significance is shown for various constructions, the results are not shown to be robust. A discussion of the results within the context of the donor search model of Chapter 3 is also provided.

CHAPTER I

INTRODUCTION

As of 2006, the amount of private contributions to US based 501(c)(3) nonprofit charities totaled around $295 billion, representing an almost 28% increase over the same figure in the year 2000 [18]. Coupled with an almost 35% increase in the number of charities between 1995 and 2005, from 572,660 to 876,164, a picture begins to emerge of a rapidly growing sector, with both increased market size and increased competition. While the increased funding is beneficial to the sector at large, whether or not increased competition is benefical remains an open question. Giving should be a powerful and satisfying act, both for the donor and the recpient, and as Clinton [23] discusses, if done correctly can be a powerful and impactful experience for both. However, as Paul Light notes [40] one of the side effects of the growth expolosion, particularly from the donor perspective, is increasing complexity in the decision process, making it harder to choose which organizations to fund so as to maximize the giving experience. When one considers that donors often times contribute to chartiable goods of which they do not directly benefit, the question of how one ascertains the quality of such goods adds an additional layer of complexity to the decision problem. At its core this dissertation examines the role of information, particularly as it relates to proxies for quality, and how it effects both the donor and organization decision processes. Building on the foundational work that deals with the economics of altruism and philanthropy I propose two models, one of signaling and one of search, to illuminate the effects of information and increased competition within the voluntary nonprofit sector.

Chapter 2, of which this dissertation was originally motivated, begins by considering the context of competition within the sub-sector of international humanitarian relief organizations. It has been observed, primarily anecdotally, that humanitarian relief events tend to spawn highly competitive environments in which organizations compete with one another for publicity and funding, often times to the detriment of effective resource utilization. This result is partly a function of the highly decentralized environment in which these organizations operate, as outlined in Figure (1), but the question persists as to why, if the ultimate goal is that of relief provision, do these organizations compete in such a manner? I posit that the competition is largely a function of the nonprofit's dual objectives (fundraising and service provision), and their inability to credibly pass themselves off as being quality organizations if they do not undertake this competitive ritual. In this respect, a signaling model is put forth to examine the effects of this hypothesis, and how an organization's desire to signal quality can be used to explain both congestion, as it regards the number of organizations that participate at a relief site, and as it regards how organizations distribute resources within the site.

The model is a two sided framework that assumes that the amount donors contribute to a given organization, in part, hinges on their perception of an organization's productivity level as it regards the use of donated funds. In response it is assumed that organizations, of which their are high productivity types and low productivity types, use their level of relief provision as a signal to donors of their productivity level. Relief in this sense is used as a catch-all term, but can be considered to be activities which are costly, but give the appearance, real or otherwise, of aid provision. Under the assumption that high productivity types can provide relief at a cheaper cost (more effectively), I am able to characterize both separating and pooling equilibrium, and the conditions under which each might occur. In the case of separating equilibrium, depending on the humanitarian context, it is shown that competition

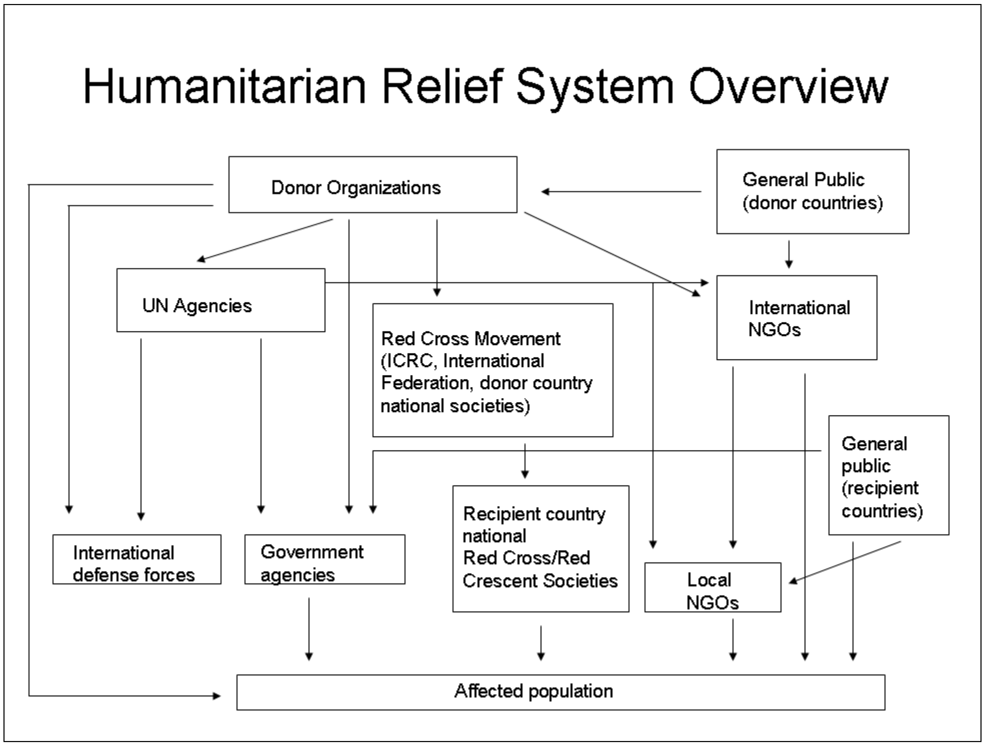

Figure 1: Overview of the Humanitarian Relief System as defined by Borton [19]

and the need to signal will induce high productivity organizations to provide relief beyond what is optimal, essentially wasting critical resources. It is also shown that given that donors' beliefs are high enough, as it regards the concentration of high quality organizations within a particular relief site, a pooling equilibrium can be induced whereby high types allow low types to pool on their optimal provision level of relief. The significance of this result is found when one considers that this donor belief level is likely to be high for those environments in which the media coverage is high, in part offering an explanation for why these areas are often heavily congested with both established and nascent organizations. Using the model as a guide, several policy prescriptions for smoothing resource and organization distribution across the humanitarian landscape are offered.

While Chapter 2 provides a foundation for how information is considered and utilized within the framework of humanitarian relief, Chapter 3 expands this notion to the broader market for humanitarian causes as a whole, and offers a complementary hypothesis for how information effects donor and organization behavior. This chapter uses economic models of search theory as a foundation, and proposes a two-stage donor search model to explain donor behavior as is regards organization selection. Whereas Chapter 2 models the effect of information on the amount a donor chooses to provide to an exogenously assigned organization, this chapter sets aside the question of the amount of the donation, and considers how the endogenous selection process might occur. Like chapter 2, the assumption is maintained that donor's care about information which allows them to make inferences about an organization's quality. However, while Chapter 2 assumes that quality is absolute, Chapter 3 assumes that organization quality is relative to individual donor preferences, and that donor's can only fully realize the quality of the match after paying some first stage cost.

In this model, after being introduced to an organization, a donor can choose whether or not to pay a cost to sample this organization through first stage engagement. The cost in this model is assumed to be an organization's monitoring cost, or transparency level. The assumption is made that donor's care about organization transparency as it makes it easier for them to ascertain the quality of the organization's work and the impact of their contribution. Resting on the fact that charitable markets consist of organizations of varying transparency and exposure levels, the assumption is made that an organization is able to manipulate both its transparency level and its exposure level (i.e. the probability of being discovered by a given donor) via its activity set. The donor's decision of whether or not to contribute to an organization in the first stage, and subsequently match with the organization in the second, are shown analytically, to take the form of reservation values. The model is subsequently used, via simulation, to explain not only the behavior of donors, but also why organizations might choose to engage in certain activities, in particular those which diverge from their core mission.

The results of the model show that while exposure and transparency are both critical to organizational success in attracting donors, the effects of exposure are absolute, while the effects of transparency are relative. In particular it is shown that effects of unilateral increases or decreases in the transparency level of an organization are largely dependent on the overall transparency level of the market. The effects in markets which are initially highly transparent are shown to be negligible, while the effects for low transparency markets are rather large for the individual organization. Additionally, it is shown that not only do individual efforts in transparency reduction increase donor market share for an individual organization, but these individual actions also have the effect of increasing overall donor participation within the market. The extent to which the results from this model are reasonable are investigated via an empirical case study in Chapter 4.

Chapter 4 concludes by conducting an empirical analysis to test the assumptions and results of the previous two chapters. Using an observational data set provided by the online charitable marketplace, GlobalGiving, I investigate the effects of transparency on both the amount of the donor's gift, and on their likelihood of repeat giving. Because of GlobalGiving's market structure, and requirements of its participating organizations, I am able to formalize the abstract notion of transparency by using the number, and recency of project updates as proxies for organizational transparency. Using project updates, along with other project related variables, a fixed effects panel regression along with an ordered logit model are used to investigate the effects of transparency on the amount of the donation. In a related test of Chapter 3's donor search model the data is coded, and modeled using multinomial logit, and conditional logit models to determine the effect of information on a donor's propensity for repeat giving. The results are complicated by discussed validity issues, and in general show that within the context of GlobalGiving proxied transparency does not appear to have a significant practical effect on either the amount of the gift or organization selection by a given donor. While some significance is shown for various constructions, the results are not shown to be robust. GlobalGiving as a marketplace is considered to be highly transparent in general, and is in part developed on the notion that transparency in giving can lead to increased engagement by the general population. Consequently, as informed by the analysis of Chapter 3, it is not surprising that within market transparency effects appear to be negligible in most of the analysis.

Chapter 5 concludes with a discussion of future work and extensions, as derived from the signaling and search models. While analysis of the GlobalGiving data is an important first step in verification, comparison of the results across more diverse populations and organizations would yield more conclusive results. Additionally, both models are amenable to experimental testing, the design and implementation of which will be critical going forward if the results are to help shape institutions and policy within the nonprofit sector.

CHAPTER II

SIGNALING IN HUMANITARIAN RELIEF

2.1 Introduction

Since the end of the Cold War, the presence of International Non-Governmental Organizations (INGOs) and Non-Governmental Organizations (NGOs) has increased rapidly, with the former being around 400,000 in number at the beginning of 2001 [7]. These organizations exist for a variety of reasons, among which include general purpose humanitarian relief and development in disaster and crisis situations. What makes these organizations distinct from traditional firms is that their primary purpose is altruistic in nature. Inevitably, however, these relief organizations must dedicate some percentage of resources to securing funds for the continued pursuit of their primary goal. As a result, these organizations operate within these two objectives, with the latter being a direct consequence of the primary objective. Given the large number of INGOs and NGOs operating in the relief sector, all with a continual need for funding, a highly competitive environment manifests itself.

Competitive environments inevitably require firms to offer more innovative and cheaper products and services than their competition in order to remain profitable. The relief sector is no different, but instead of a physical product, these organizations essentially sell their service and relief work to donors, who purchase these services for the affected populations. As a consequence, these organizations compete to sell the perception that they are the most effective and timely relief organization. While competition in traditional markets can be good for the consumer, in that it usually results in improved pricing and products, that has not been shown to be the case in humanitarian relief work. Within this context, competition offers somewhat of a paradoxical result in that it can often lead to the degradation of the primary relief objective [25][105]. Additionally, competition not only degrades primary objective performance on the individual organizational level, but it also degrades overall relief performance, in that it actively dissuades cooperation and coordination among the various NGOs.

One peculiar, but perhaps not surprising, side-effect of the competitive environment is the frequent observation of congestion in high attention relief areas, in particular during the timeframe immediately following the disaster. To be sure, much of this congestion is attributable to the desire of the relief organizations to simply provide relief, but it is the hypothesis of this chapter that a portion of the congestion can be attributable to the desire of the relief organization to distinguish itself as a high quality organization, in the hopes of attracting donor funding. In fact Simon [89], Bennett and Kottasz [16], and Brown and Minty [21] allude to exactly this behavior.

The notion of signaling in humanitarian relief is not meant to claim that relief is only provided as a means to attract donor funding. The motivation for this framing is that relief organizations must continue to fundraise in order to remain viable in a highly competitive humanitarian marketplace. In turn, fundraising can be thought of as a function of exposure and credibility. The more credible an organization is perceived to be, and the more exposure it receives, it usually follows that its ability to raise funds increases. This chapter contends that one of the primary tools that an organization can deploy to bolster both credibility and exposure is the provision of highly publicized relief, which effectively acts as a signal to donors of the aforementioned variables. In this context, the premise of this research rests on the assumption that the ability, and what some may term the necessity, of organizations to use relief as a signal effectively causes organizations to over provide in high visibility relief areas. While not necessarily harmful in isolation, this chapter advances the notion that many instances of the oft cited congestion, waste, and coordination difficulties found at relief "hot spots" can be attributable, at some level, to this signaling driver, which itself is manifested out of competitive pressures.

With respect to the hypothesis, the first task is to define an appropriate model of the system that can be used to either reject or accept the assumption presented above. There is a large body of anecdotal evidence to bring forth in support of the aforementioned statements in relation to coordination, waste, and congestion. However, while there are several theories as to the impetus behind the sub-optimal states, there has yet, to the writer's knowledge, to be a casting of the problem within the framework of principal-agent modeling, with the notion of signaling as the driver behind these undesirable outcomes. What follows is an attempt to construct a descriptive model in this light.

While the outcomes of this model can be applied across the general charitable landscape, there is some value in a specific consideration of the humanitarian relief context. In particular, many other charities are able to manufacture media events that can showcase their work, or the results of their work, in a highly visible manner (i.e. breast cancer walk for survivors, Habitat for Humanity, homeless shelters with food lines, etc...). Humanitarian relief organizations, especially those of the international variety, have a harder time making tangible the work that they do, with their work often times occurring thousands of miles away from those who they depend on to fund it, effectively offering to the potential donor what can be considered a credence good [30]. Consequently, signaling is that much more important within this realm if one considers that these organizations can only provide seemingly verifiable signals through carrying out their work in a highly visible manner. Otherwise, they must rely on what they tell others about the work that they do to fuel confidence. Thus, while other charitable organizations have several verifiable signals to employ, relief organizations are left with a subset of those. It is this distinction, perhaps most clearly understood as a difference in signaling capabilities, that makes relief organizations more dependent on signaling through their work than others.[1] While all charities face, to some extent, an information asymmetry problem, and the need to signal, it is considered that the nature of humanitarian relief and development work may warrant special attention. Moreover, this work lays the foundation for several testable outcomes about both organization and donor behavior, specifically:

- Donor beliefs about the proportion of high quality organizations participating in an area directly influences the existence of dominant pooling equilibrium. The existence of which leads to a more attractive funding environment for lesser quality organizations.

- The level of relief provided by an organization directly contributes to the amount of funding received by that organization.

- Depending on the environment, organizations give more than they would at optimality, leading to congestion in resources.

These issues, along with several policy recommendations are developed throughout the chapter. Section 2.2 provides further background and framing of the problem through a review of related literature. Sections 2.3 presents a general model of signaling in humanitarian relief, defines related solution concepts, and characterizes the relevant equilibrium. Section 2.4 interprets the results of section 2.3 within the framework of the considered problem, and offers some potential policy implications. Section 2.5 concludes with a summary of results and the discussion of several several extensions.

[1] It should be noted that this is not just the case for humanitarian relief organizations, but for any charitable organization that operates within an international framework, where it draws funds from a base distinct from it conducts their work.

2.2 *Background and Literature*

2.2.1 Evidence of Competition in the Humanitarian Relief Space

The problem of coordination and competition among NGOs, specifically those of the humanitarian relief variety, has been fairly well documented over the past two decades. What follows is an attempt to trace the origins of this coordination problem, discuss relevant cases related to this problem, and identify theories which deal with both the source and potential solution to the problem.[2] Much of the work and analysis has centered around qualitative observations and remedies rooted in organizational theory, leaving open the space for treatment from a more quantitative perspective.

Coordination, or the lack thereof, has been a generally recognized problem among NGOs, UN entities, practitioners, and academics alike [63]. Most view coordination, as a necessity in achieving the most effective humanitarian response possible. Willitts-King and Harvey [105] refer to coordination affects in helping to prevent corruption. Lipson [54] and Stephenson [93] espouse coordination's benefit to improved efficiency. Macrae and Harmer [57] outline the necessity of coordination from the standpoint of dependency, in that by the sheer size of the work, no one organization can effectively complete the task by itself, thus necessitating some level of coordination. The most commonly used working definition of coordination [73] [96], is that provided by Minear:

"*[Coordination is] the systematic utilization of policy instruments to deliver humanitarian assistance in a cohesive and effective manner. Such instruments include: (1) strategic planning; (2) gathering data and managing information; (3) mobilizing resources and assuring accountability; (4) orchestrating a functional division of labor in the field; (5) negotiating and maintaining a serviceable framework with host political authorities; and (6) providing leadership. Sensibly and sensitively employed, such*

[2] While in theory there is a distinction to be made between the terms, coordination, competition, and cooperation, they are used rather loosely in this initial context to describe organizations willingness to work together along the lines outlined by Minear.

instruments inject an element of discipline without unduly constraining action." [64]

There are several thoughts on why this lack of coordination occurs, and where some of the potential solutions might be found. Organizational insecurity, from the standpoint of funding, as outlined by Cooley and Ron [25], is given as a contributor to increased competition. In analyzing this increased competition and its effects on coordination and efficiency outcomes Cooley and Ron draw from the theory surrounding the New Economics of Organization. It is their contention that the increased competition, and the constant search for the next funding source causes organizational efficiency to decrease, coordination to decrease, and the number of publicity seeking organizations to increase in high media attention areas. Natsios [68] reinforces this through his contention that the cheapest way for relief organizations to fundraise is to provide early relief in highly visible areas . Similarly, Smillie [90] supports the notions of NGO insecurity as it concerns short-term funding, and the reliance on the media via participation in high-visibility areas as a fundraising tool. Cooley and Ron, highlight the competition problem through the following:

"*The more contractors there are, the more contract uncertainty increases for individual organizations. As a result, contractors will do their utmost to beat out competitors and promote their own projects, regardless if cooperation would actually improve project quality or help the recipient. The presence of multiple donors, moreover, increases the ability of aid recipients to play contractors and donors off one another for opportunistic gain.*" [24]

In his chapter on coordination Minear [63] devotes a significant amount of space to the congestion issue, in a sense, signaling a divide of the coordination problem into a macro- and micro-context. The micro-perspective is a question of how organizations coordinate once they have arrived at a designated disaster area. The macro-context is concerned with the issue of how relief organizations choose which areas to participate in, and as a consequence, how might organizations most effectively distribute themselves across the humanitarian landscape. Minear strongly suggests that the landscape might be better served if congestion, or overcrowding, in these areas could be avoided, thereby facilitating coordination at the micro-level.

While Cooley and Ron approach the problem through an organizational perspective, their primary analysis focuses on contracting incentives and opportunities that arise in the market due to information asymmetries. Stephenson [93] however, focuses on the attribute of inter-organizational trust and its affect on organizational willingness to coordinate. Stephenson eschews the principal-agent, or top-down, coordinating solutions explored by others [11] and proposes viewing the humanitarian enterprise in terms of a social network. He cites other organization scholars that recognize trust as an important factor in inter-organizational coordination, and subsequently asserts its importance in motivating coordination in the humanitarian sector. He contends, under a social network view, trust-building lies at the core of a solution to the problem of coordination in humanitarian emergencies. Difficulties in building trust across organizations is derived in large part from the uncertain and ephemeral nature of humanitarian work. Although certain organizations may be stalwarts in the relief process the staff turnover is relatively frequent, making it difficult to establish trust based via companionship and competence. Stephenson [94] reinforces this claim through field interviews with those who support the proposition that trust building, in the absence of top-down command, is essential in aiding coordinating efforts.

Staying within the realm of Organizational Theory, Lipson [54] explores concepts from Institutional Theory and how they can be brought to bear on problems of coordination among humanitarian organizations. Lipson contends that many of the frameworks, specifically organizational field theory and organized hypocrisy, developed by organizational theorists to deal with coordination can be readily applied to the issue of humanitarian relief coordination. Essentially conducting a preliminary analysis of their appropriateness, Lipson urges further research into insights provided through the application of institutional frameworks.

While there exists a rather significant body of work on the NGO coordination problem in general, there also exists a set of literature focused on case studies of specific relief events. Much of this work provides a discussion of coordination, both its successes and failures, within the context of an actual disaster or humanitarian emergency. Cooley and Ron [25] provide three qualitative case studies to support their organizational insecurity hypothesis presented earlier. Among these cases are included: (1) a case of "technical assistance in Kyrgyzstan", (2) a case of "competitive bidding and Refugee Relief in Goma," and (3) a case of "Multiple Principals and Bosnia's POW's". Additionally, Stockton [96] provides an analysis of coordination within the context of Afghanistan.

In their case study of the Mozambique Floods, Moore et al. [66], use a measure of centrality to quantify organizational coordination within the context of the disaster, and subsequently conclude that those organizations with higher centrality scores, on average, had higher relief and recovery period beneficiaries. Wood [107] describes an event, the Bam earthquake disaster, in which over 200 international organizations arrived within the first two weeks. There were some successes as it concerned the willingness to coordinate as exemplified through shared use of supplies, along with an attempt at a functional division of labor and zoning within the relief area. However, while some initial attempts were there, the coordination ultimately fell short of its goal, as some organizations were assigned areas which they could not handle, along with a lack of information sharing which resulted in, among other things, wasted efforts in repeating work.

In a more recent example, Bennett et al. [15] provide a case study of the aftermath surrounding the tsunami of December 2004 in Maldives, Indonesia and Sri Lanka. Key observations include: displeasure among INGOs at the UN's role in sectoral leadership, congestion at the relief sites due to a large number of INGOs participating in the relief theater, and the unwillingness of some INGOs to share information. Among the various recommendations made, Bennett et al. recommend looking into the feasibility of establishing a certification process to distinguish responsible NGOs.

Reindorp and Wiles [73], along with Donini and Niland [31] focus on evaluating coordination from the perspective of the UN. Both reports, and in the case of Donini and Niland, specifically within the context of Rwanda, outline the need for intra-organizational coordination at the UN. Both call for, at some level, a restructuring or clarifying of mandates and responsibilities among the UN's relief response entities.

There is a rather large body of work concerning coordination of humanitarian relief organizations. Much of the work has centered on evaluation of the problem through both a case study approach, and methodology borrowed from organizational theory. While there has been study of the problem under a principal-agent framework, there has not been much in the way of game theoretical analysis of this framework. Centrality scores notwithstanding, the literature fails to provide for a quantitative approach to the problem of coordination. Consequently, the problem lacks a treatment of policy that may be recommended by such an approach, or at the very least a verification of aforementioned solutions such as trust and improved contracting.

2.2.2 Giving and Signaling

There has been much theoretical work done over the last few decades in the area of philanthropy, from an economics perspective. Most of the work has focused on the donor side of the market, but there has also been quite a bit of study of the marketplace from the charitable organization perspective. This chapter attempts to build on some of the work found in this area through the application of the well developed work in economic signaling. A brief overview of the economics literature that informs this work is considered below.

Spence's [91] seminal 1973 paper on job market signaling seeks to formally define the notion of market signaling in economics. His work lays at the foundation for much of what is considered in this paper, and has pathed the way for many useful application derivatives. In what can be considered an extension of Spence's work, Crawford and Sobel [27] provide a model of strategic communication, specifically bargaining situations in which each side has different information. They explore how much information will be revealed as it relates to the agents' similarity of interests. For a more thorough treatment of the historical development of signaling literature Riley [76] traces the origins of the literature through a comprehensive review of its foundations and subsequent contributions. Riley cites four papers as having set the foundation for the field, in addition to Spence's work he lists, Vickery [101], Mirrlees [65], and Akerlof [1].

The notion of signaling in philanthropy and charitable giving is not a novel concept, and others have considered its role in altering actor behavior within the market. Glazer and Konrad [38], Vesterlund [100], Romano and Yildirim [77], and Andreoni [5], all put forth similar arguments that consider signaling as an impetus for giving. Their arguments rest on the notion that donors use their charitable contributions to signal something about themselves, usually income. The contention made in these papers, specifically Glazer and Konrad, is that while wealth can be signaled to some extent through private goods, public goods can at times offer more exposure and a better opportunity to signal wealth. Additionally, the latter three papers consider the notion that signaling, specifically in the form of leadership giving, can cause others to increase their opinion of the quality of a particular charity or cause.

In perhaps the work most closely related to the presented model, Reinhardt [74] advances the notion of signaling's role in matching donors and nonprofits. Reinhardt presents a binary decision game (signal or don't signal) that focuses on the effectiveness of signaling from an organizational perspective. Reinhardt considers a suite of signals, among which include: age, religious affiliation, professionalism, accountability, legal registration, higher-degrees of donor accessibility, and third party audits. She puts forth that "If the process of sending and reading signals is efficient, funding decisions will tend toward optimal outcome in which only effective agencies survive." This is in line with the presumptions of this model, but this paper extends Reinhardt via exploration of how the inefficiency occurs, how it changes dependent on the environment in which the organization is operating, and the consideration of one signal in particular. She concludes with the following, "Multivariate analysis shows that donors channel their money to organizations exhibiting higher levels of reliability, accessibility, credibility, and fundraising specialization."

Much of the work in applied signaling, particularly as it concerns charitable giving, can be considered in the same context as the work that seeks to link media, advertising and donations. Bennett and Kottasz [16] through interviews of two hundred people come to conclusions on how media representation of disasters induce people to give. In particular, it was concluded that the way the media covers a particular disaster has a strong effect on how the general public donates. Simon [89] tells us that aggregate donations increase in response to "big news" events, but does not offer much in the way of individual organization fundraising in response to these same events. Tisdell and Wilson [97] present research on willingness-to-pay (WTP) for the conservation of wildlife species, which offers a direct parallel to what would be WTP for certain relief instances. Their results showed that poorly known species may obtain less conservation than they deserve due to a lack of public exposure, emphasizing the importance of the media in influencing charitable decisions.

From a theoretical perspective Milgrom and Roberts [62] extend Nelson's seminal work [70] on advertising as information. Where Nelson considers the value of advertising on informing consumer opinion of a particular product, Milgrom and Roberts consider both advertising and price as dual signals of quality. Of particular value is the framework they put forth for understanding solution methods for multi-signal games.

Particularly important to the motivation of the presented model, is the work on philanthropy, altruism, and giving from an economic perspective. This work primarily informs the donor side of the philanthropy market, and is concerned with the impetus behind charitable giving. Wolpert and Reiner [106], Rose-Ackerman [80], and Andreoni [4] offer attempts to characterize what is meant by the philanthropic market in the context of economics through literature reviews and commentary. Bekkers and Wiepking [13] survey over 500 publications related to philanthropy with a focus on the questions of; who gives, how much do they give, and why do they give. Specifically as it relates to why people give, they identify eight factors as important forces that drive giving: (1) awareness of need; (2) solicitation; (3) costs and benefits; (4) altruism; (5) reputation; (6) psychological benefits; (7) values; (8) efficacy.

The question of why people give, in an economic setting, inevitably leads to the question of what does a giver's utility function look like. Several theories have been put forth along this line. Traditional public goods literature says that people will give because they benefit in some way from the aggregation of all contributions to that good, which in this setting would be relief. Cornes and Sandler [26] offer a thorough treatment of public goods theory. In addition to theories of prestige and wealth signaling mentioned above, Andrenoi, Duncan, and Harabaugh offer contributions to the discussion of motivations in giving. Andreoni's [3] work, which informs the donor side of the presented model, puts forth the notion of *warm-glow* or impure altruism, suggesting that in addition to the benefit the donor receives from the public good there are also private benefits that the donor experiences from the act of giving itself. The inclusion of the private benefits to donors from their own contributions altered the assumptions from traditional public good theory in a dramatic way. In particular, Andreoni concludes with, "By assuming that individuals are not indifferent between gifts made by themselves and gifts made by other individuals or the government, we conclude that redistributions to more altruistic people from less altruistic people will increase total provision, that crowding out will be incomplete, and that subsidies can have the desired effect". Crumpler and Grossman [29] confirm Andreoni's theory through experimental testing. In part based on Andreoni's consideration of private benefits, Duncan [32] and Harbaugh [43] are able propose models of donor giving that rest on private motivations. Duncan asserts that people give, in part, based on the perceived impact of their donation. This work suggests that the same donation to different organizations may effect the donor differently depending on the level of impact the donation can provide. Harbaugh, similar to the signaling models presented above, puts forth a model of prestige that is based on the consideration of warm-glow.

While the presented literature spans several different disciplines it all actively informs and influences the presented model. The literature from the organizational behavior perspective helps to motivate the considered problems of waste, inefficiency in relief provision, and difficulties in coordination. The economics literature provides a basis from which to begin development of a comprehensive model. The work on the donor side of the equation is critical in understanding what drives giving and altruistic behavior, which without, there would be no humanitarian marketplace of which to speak. The signaling literature provides an established methodological perspective allowing for both the closure of the model, and the subsequent analysis of behavior and outcomes.

2.3 The Signaling Model

The initial model assumes a world in which there are disastrous events, people that care about the effects of them, and organizations which work to reverse the effects of these events. As such, two classes of agents are considered, donors and relief organizations, and a set of relief areas or causes which are served by these agents. Donors effectively act through relief organizations to help ameliorate a particular cause or set of causes. The purchase of relief by donors via donations to relief organizations can be thought of as a type of public good. Let i define an individual donor in the set $Donors$, such that $i \in Donors$ where the set has cardinality of N. Similarly, let j denote individual relief organizations in the set RO, with cardinality of M, and k for individual relief areas in the set RA with cardinality P, when needed. The model is a one period signaling model in which the amount of relief provided by an organization acts as a signaling mechanism to donors, allowing them to ascertain the productivity of an organization, which can be of high type ($\bar{\theta}$) or low type ($\underline{\theta}$).[3] What follows is a high-level overview of the game dynamics, accompanied by further discussion of the individual actors and their strategies.

2.3.1 Order of Events

Nature takes two turns at the beginning, first assigning each relief organization a type $\theta \in \{\bar{\theta}, \underline{\theta}\}$, observable only to the individual organizations, where $Prob\{\bar{\theta}\} = \lambda$ and $Prob\{\underline{\theta}\} = 1 - \lambda$. Second, nature assigns an organization to each donor in accordance with the donor selection rule. Given types, each organization makes a decision about how much relief to allocate toward a selected cause or area. Viewing these allocation decisions, each donor makes a determination as to the type of each organization and makes a donation accordingly. All actions occur in a "one-shot" framework. Figure (2) provides an extensive form representation of the game.

2.3.2 Donors and Relief Organizations

Donors

[3]The term relief is rather generic, and will remain so throughout in order to ease computation and analysis of the model. In more nuanced terms relief could be considered to be labor, food supplies, financial aid, logistical support, etc. The assumption is made that some monetary value can be associated with each of these items, and can be aggregated on a macro-level and thought of as the generic relief mentioned here.

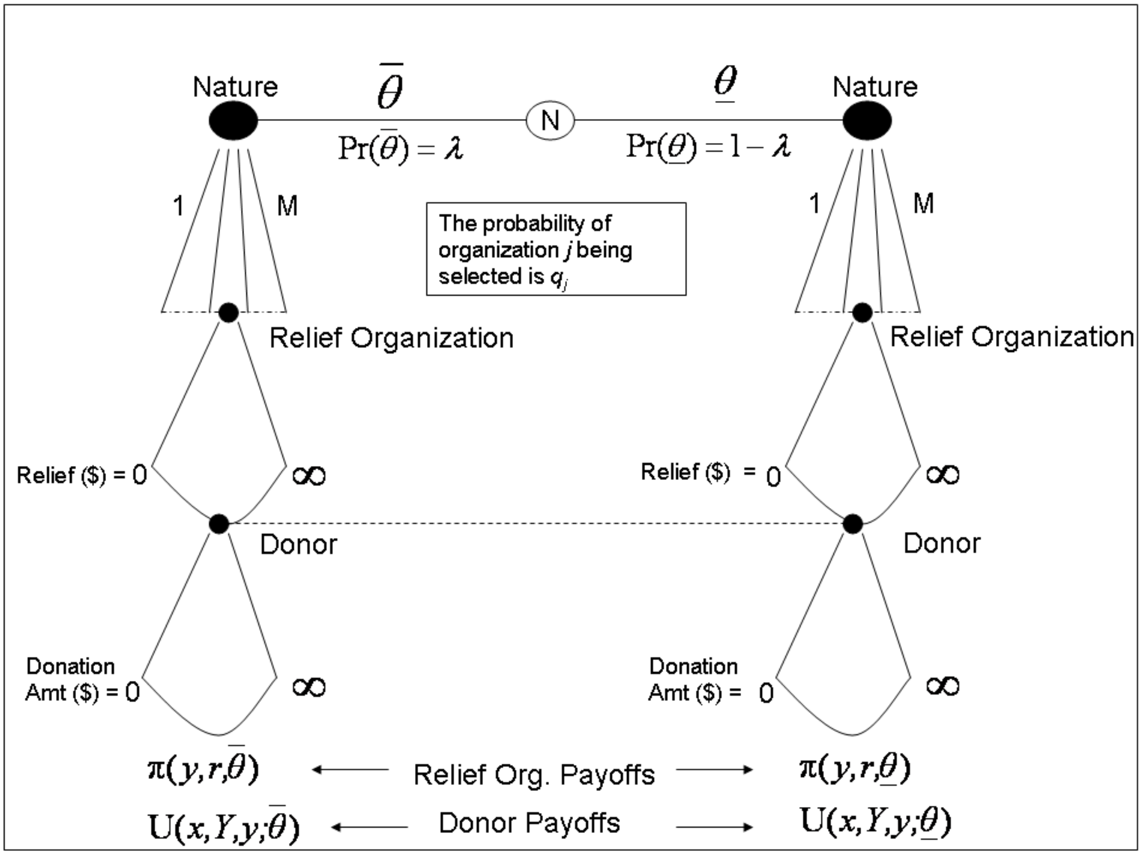

Figure 2: Extensive Form Representation of Signaling in Humanitarian Relief

Donors in the model are considered to be heterogeneous in their preferences over causes, but homogeneous in preferences over productivity.[4] As has been discussed, there is quite a large body of quantitative work on the donor behavior, and the formulation of their preferences in giving to charitable organizations. This model does not attempt to add to this body of work, but rather uses this work as a justification of the assumption that giving philanthropically does enter an individual's utility function in some fashion. In this sense, an individual donor i is assumed to have the following utility function,

[4]What is meant by this will become more clear later on. For our purposes now it essentially means that a given donor may prefer one set of organizations over another for the *type* of work that they do, but within that set of organizations that do similar work all donors will always give at least as much to the organization that it views to be the most productive as it will to all others.

$$U_i(x_i, Y_1, \ldots, Y_M, y_{i1}, \ldots, y_{iM}; \theta_1, \ldots, \theta_M) \tag{1}$$

where $U_i(\cdot)$ is assumed to be strictly quasi-concave, x_i represents private consumption, and θ_j represents the productivity of the relief organization j. Additionally, $Y_j = \sum_{i \in Donors} y_{ij}$ is defined as the total amount of donations provided by all donors to relief organization j, where $y_{ij} \in \Re_+$ represents the donation of donor i to organization j. Given the utility function defined by (1), his budget constraint, defined by a vector of prices $\mathbf{p} \in \Re_+^M$ associated with giving to an organization and his budget $w_i \in \Re_+$, donor i sets out to solve (2).

$$\max_{x_i, y} U_i(x_i, Y_1, \ldots, Y_M, y_{i1}, \ldots, y_{iM}; \theta_1, \ldots, \theta_M) \tag{2}$$

$$s.t.\ x_i + p_1 y_{i1} + \ldots p_M y_{iM} \leq w_i$$

The initial presentation we considers a world in which the donor selects one relief organization, $\hat{j}$, for which to provide a donation, via the donor decision rule defined below. As such, the maximization problem (2) can be rewritten as,

$$\max_{x_i, y_{i\hat{j}}} U_i(x_i, Y_{\hat{j}}, y_{i\hat{j}}; \theta_{\hat{j}}) \tag{3}$$

$$s.t.\ x_i + p_{\hat{j}} y_{i\hat{j}} \leq w_i$$

Furthermore, the public effects on utility, $Y_{\hat{j}}$, are initially excluded from the model, such that the donor only receives a warm-glow from his contribution to the organization. While slightly limiting, this assumption does not detract from the primary analysis, and can in some instances, particularly those associated with relief giving, represent donor giving behavior.[5]

[5] Alternative utility formulations, such as those put forth by Andreoni, Vesterlund, and Harabaugh may alter donor giving behavior. The extent to which characterization of the utility function alters the presented analysis will be considered as an extension

$$\max_{x_i, y_{i\hat{j}}} U_i(x_i, y_{i\hat{j}}; \theta_{\hat{j}}) \tag{4}$$

$$s.t.\ x_i + p_{\hat{j}} y_{i\hat{j}} \leq w_i$$

Donor Decision Rule: *Before observing signaling levels the donor chooses a relief organization at random. After observing the organization's signal the donor must then donate funds based on that signal.*

An explicit function is not defined for $U_i(\cdot)$ as it does not advance the development of the model, beyond what is outlined above. What is necessary is that there be levels of giving, not necessarily unique, on behalf of each donor when confronted with the belief that a relief organization is of a particular type. More specifically, for this model, given beliefs about the type of a relief organization, $\bar{\theta}$ or $\underline{\theta}$, a donor i will contribute either $\bar{y}$ or $\underline{y}$ to the respective organizations, as defined by equations (5) and (6). While not defining exact values for either level, the condition that $\bar{y} > \underline{y}$ is added. Formally, the donor's strategy can be defined as a function $g_i : \Re_+ \rightarrow y_i \in \Re_+$.

$$\bar{y} = \arg\max_{y_{ij}} U_i(w_i - p_{\hat{j}} y_{i\hat{j}}, y_{i\hat{j}}; \bar{\theta}_{\hat{j}}) \tag{5}$$

$$\underline{y} = \arg\max_{y_{ij}} U_i(w_i - p_{\hat{j}} y_{i\hat{j}}, y_{i\hat{j}}; \underline{\theta}_{\hat{j}}) \tag{6}$$

Relief Organizations

In addition to the donors, relief organizations are also considered, of which there are two types, a high productivity organization ($\bar{\theta}$) and a low productivity organization ($\underline{\theta}$), where $\bar{\theta} > \underline{\theta}$, and *ex ante* probability defined as $\text{Prob}\{\theta_j = \bar{\theta}\} = \lambda$ and $\text{Prob}\{\theta_j = \underline{\theta}\} = 1 - \lambda$.[6] Dependent upon both its type, and the expected donations to

[6]Differences in θ can be explained, in practice, through organizational capacity, expertise, and relationships. This chapter does not attempt to explicitly define values for θ, nor how they might be derived, but builds on the knowledge that much as in the private sector, differences do exist. An organization's ability to leverage its past expertise and network in a time of crisis will almost certainly guarantee more efficient use of resources than other newly formed entities.

be received from donors, a relief organization j makes a decision about which of the P relief areas to commit resources to, and at what level. This decision is represented through the relief organization's strategy $f_j : \{\bar{\theta}, \underline{\theta}\} \times \Re_+^P \rightarrow \mathbf{r_j} \in \Re_+^P$. The initial analysis considers only one relief area such that, $f_j : \{\bar{\theta}, \underline{\theta}\} \times \Re_+ \rightarrow r_j \in \Re_+$.[7] In this one area setting an initial objective function,$\pi_j(y, r, \theta)$, is posited for the relief organization j.[8]

$$\pi_j(y, r, \theta) = (y + r) - g(r, \theta) \tag{7}$$

Where $(y + r)$ represents the benefits accrued to the relief organization via donations (y), and relief provided (r). $g(r, \theta)$ is the disutility to the organization for providing relief, and is defined such that; $g_r(r, \theta) \geq 0$ and $g_{r\theta}(r, \theta) \leq 0$ for all $r \geq 0$, and $g_{rr}(r, \theta) > 0$ and $g_\theta(r, \theta) < 0$ for all r.[9] $g(r, \theta) = \frac{\mu r^2}{\theta}$ is defined, where $\mu \in \Re_+$ represents the utility a relief organization receives from actually providing the relief, thus abating some of the disutility that results from relief provision.[10] Equation (7) now becomes (8).

$$\pi_j(y, r_j, \theta_j) = (y + r_j) - \frac{\mu r_j^2}{\theta_j} \tag{8}$$

[7]The one area setting is justified via the initial context and problem considered. At issue is the use of signaling in a particular relief area, and its impact on over-provision of relief and waste, as a result of organizational aversion to cooperation. The same results would hold for a multi-area analysis, but the outcomes would be dependent upon the parameters associated with a particular area. The behavioral analysis is focused not on the organization's decision over which area to participate in, but *how* to participate in a given area. This micro-level consideration does, however, offer some insight into the macro-level question of how might organization's choose areas.

[8]While distinct in form, the organization objective function can be considered to be related to the empirically verified revealed nonprofit objective function proposed by Steinberg [92]. He offers that organizations have dual motivators akin to those considered in the introduction. As such, depending on which objective an organization places emphasis on it can be considered either a "service maximizer" or a "budget maximizer."

[9]Thus, the first derivative implies that the relief organization's disutility increases in relief. Additionally, $g_{rr}(r, \theta) > 0$ implies that this aversion is larger given the current level of relief r. Higher values of θ are more desirable, as θ increases it becomes cheaper for the relief organization to provide the same level of relief, and as implied by $g_{r\theta} < 0$, the marginal disutility of providing relief also decreases in θ.

[10]$g_r(r, \theta) = 2\mu r\theta^{-1}$; $g_{rr}(r, \theta) = 2\mu\theta^{-1}$; $g_\theta(r, \theta) = -\mu\theta^{-2}r^2$; $g_{r,\theta}(r, \theta) = -2\mu\theta^{-2}r$.

The function takes into account the dual motivators of the relief organization, which were posited in the introduction, namely expected donations and relief provided. The function is linearly increasing in donations, but is quadratic in relief provided. What is unique about this objective function as opposed to that of a traditional firm is that, depending on the cost function and reservation profit level, the relief organization may still like to provide its "product" at some level, even in the absence of demand from donors.[11] A traditional firm, facing zero demand would not find it economically beneficial to produce anything at all. The disconnect occurs because the relief organization is essentially serving two audiences, the donors and the affected populations in the relief areas. As discussed in the introduction, relief organizations have altruistic motivations to serve, so even when the donor audience disappears there is still a desire to serve the affected population to the extent that it is able to in the absence of increased donor funding.

While equation (8) is a basic representation of an organization's objectives, it is lacking a dependence on the number of donors, N, and organizations, M, in the system. In adding the impact of the system to the objective function, the organization's function must be recast as an expectation. Specifically, the presence of additional relief organizations is felt in terms of an individual organization's probability of receiving funding. Assuming the decision rule outlined above, q is the probability of an organization being selected as a donor recipient where, given M relief organizations let $q = \frac{1}{M}$, such that each organization has a fair chance of being selected *a priori*. For a relief organization, expectation is calculated via M Bernoulli trials. In a situation with N donors and M relief organizations an organization conducts these Bernoulli trials, one with each donor, as a determinant on whether or not it will receive the contribution of the donor. A success vector, $\mathbf{ro} = (b_1, b_2, b_3, b_4, b_5)$, $\mathbf{ro} \in \{0,1\}^N$, is created for each organization where each of the N elements is a binary random

[11] $\pi_j(\theta_j)^{res}$ is the reservation *profit* level afforded to relief organization j of type θ_j

variable, where 1 denotes selection, and 0 denotes rejection. Defining the chances of success by q leads to $\mathrm{E}[b_1] = q$, $\mathrm{E}[b_2] = q$, …, $\mathrm{E}[b_N] = q$. As such, the expectation of the total number of donors picking an organization is Nq. Consequently, the expected payoff to an organization participating in a system with N donors and M relief organizations can be represented as in equation (9), or equivalently (10).

$$\mathrm{E}_{MN}[\pi_j(y, r, \theta)] = Nqy + r - \frac{\mu r^2}{\theta} \tag{9}$$

$$\mathrm{E}_{MN}[\pi_j(y, r, \theta)] = (N/M)y + r - \frac{\mu r^2}{\theta} \tag{10}$$

2.3.3 Solution Concepts

The hypothesis proposes that $r \in R_+$ is an observable signal of an organization's productivity, θ, to the donor. As such, the question that immediately arises is how does the equilibrium outcome of this game change when r is taken as a signal of the productivity level and when it is not. The *perfect Bayesian equilibrium* (PBE) solution concept is used to answer this question and characterize equilibrium resulting from the game. Define $R = \Re_+$ as the set of possible messages, with $r_j \in R$ being a specific message. Define Θ as the set of possible types, with $\theta \in \Theta$ being a specific type. The following requirements must be satisfied to establish a PBE.

Signaling Requirement 1 *After observing any message r_j from R, the Donor must have a belief about which types could have sent r_j. Denote this belief by the probability distribution $\lambda(\theta|r_j)$, where $\lambda(\theta|r_j) \geq 0$ for each θ in Θ, and*

$$\sum_{\theta \in \Theta} \lambda(\theta|r_j) = 1 \tag{11}$$

Signaling Requirement 2R *For each r_j in R, the Donor's action $y^*(r_j)$ must maximize the Donor's expected utility, given the belief $\lambda(\theta|r_j)$ about which types could have sent r_j. That is, $y^*(r_j)$ solves*

$$\max_{y_i \in Y} \sum_{\theta \in \Theta} \lambda(\theta|r_j) U_{donor}(y_i(r_j); \theta) \tag{12}$$

Signaling Requirement 2S *For each θ in Θ, the Relief Organization's message $r^*(\theta)$ must maximize the Relief Organization's utility, given the Donor's strategy $y^*(r_j)$. That is, $r^*(\theta)$ solves*

$$\max_{r_j \in R} \pi_{relieforg}(r_j, y^*(r_j), \theta) \tag{13}$$

Signaling Requirement 3 *For each r_j in R, if there exists θ in Θ such that $r^*(\theta) = r_j$, the Donor's belief at the information set corresponding to r_j must follow from Bayes' rule and the Relief Organization's strategy:*

$$\lambda(\theta|r_j) = \frac{\lambda(\theta)}{\sum_{\theta \in \Theta_{r_j}} \lambda(\theta)} \tag{14}$$

Θ_{r_j} is the set of types that would send r_j in optimality.

Definition: A pure-strategy PBE in a signaling game is a pair of strategies $r_j^*(\theta)$ and $y^*(r_j)$ and a belief about types $\lambda(\theta|r_j)$ satisfying the above requirements.

2.3.4 Equilibrium

As a baseline, consider the instance in which r is not taken as a signal, and so any message sent by the relief organization has no effect on the *ex ante* beliefs of the donor. Assuming the donor, under complete information, would offer $\bar{y}^*$ to a $\bar{\theta}$ type organization and $\underline{y}^*$ to a $\underline{\theta}$ type organization, then a donor will offer $\hat{y}_i^* = \lambda\bar{y}^* + (1-\lambda)\underline{y}^*$ in equilibrium when no signaling is allowed.[12] The relief organization will only pursue this donation if there exists some relief level r such that $\pi_j(\theta_j)^{res} \leq ((N/M)\hat{y}^* + r) - \frac{\mu r^2}{\theta}$. While the prospect of one donation may not be enough, an aggregate of the donations to this relief organization may be enough to induce them

[12]The assumption is made about $U_i(\cdot;\theta)$ such that this is true (i.e. $\max U_i(\cdot; E[\theta]) = E[\max U_i(\cdot;\theta)]$)

to participate. As more donors are introduced, specifically N, the condition becomes accept if $\pi_j(\theta_j)^{res} \leq r - \frac{\mu r^2}{\theta} + (N/M)\sum_{i=1}^{N} \hat{y_i}^*$, for some r. Assuming identical utility functions across the N donors, the expression yields the following condition on the number of donors required for a particular market to *open up* for a relief organization $\sqrt{\frac{\pi(\theta)^{res} + \frac{\mu r^2}{\theta} - r}{q\hat{y}_i^*}} \leq N^*$. In other words, N^* donors must be present within a given market for an organization to be willing to participate.

Proposition 1: From equation (10) the organization, of type θ, will provide $r^* = \frac{\theta}{2\mu}$ in an optimal market.

Proposition 2: If relief levels, r, are observable, then there exists a separating equilibrium in productivity levels such that $\bar{y} = y'(r(\bar{\theta}))$ and $\underline{y} = y'(r(\underline{\theta}))$, where $r(\bar{\theta}) = \bar{r}'$ and $r(\underline{\theta}) = \underline{r}'$.

Proof. Satisfaction of the *single-crossing* or *sorting* condition on the objective functions of types $\bar{\theta}$ and $\underline{\theta}$ are necessary for the existence of a separating equilibrium. In general, the sorting condition, must satisfy [35], for all $k \in \{1 \ldots n\}$, either $\frac{\partial}{\partial\theta}(\frac{\partial u_1/\partial x_k}{\partial u_1/\partial t}) > 0$, or $\frac{\partial}{\partial\theta}(\frac{\partial u_1/\partial x_k}{\partial u_1/\partial t}) < 0$. When applied to $\pi(y,r,\theta) = y + r - \frac{\mu r^2}{\theta}$, yields the following condition, for all r, and $\theta \geq 0$: $\frac{\partial}{\partial\theta}(\frac{\partial\pi/\partial r}{\partial\pi/\partial y}) = \frac{\partial}{\partial\theta}(1 - \frac{2\mu r}{\theta}) = \frac{2\mu r}{\theta^2} > 0$. Thus, establishing the single-crossing result in the positive quadrant. $\square$

If signals $\bar{r}'$ and $\underline{r}'$ are to separate, then the following conditions must be satisfied ($g(r,\theta) = \frac{\mu r^2}{\theta}$):

$$\pi^{res}(\bar{\theta}) \leq (N/M)\bar{y}^* + \bar{r}' - g(\bar{r}', \bar{\theta}) \tag{15}$$

$$\pi^{res}(\underline{\theta}) \leq (N/M)\underline{y}^* + \underline{r}' - g(\underline{r}', \underline{\theta}) \tag{16}$$

$$(N/M)\bar{y}^* + \bar{r}' - g(\bar{r}', \bar{\theta}) \geq (N/M)\underline{y}^* + \underline{r}' - g(\underline{r}', \bar{\theta}) \tag{17}$$

$$(N/M)\underline{y}^* + \underline{r}' - g(\underline{r}', \underline{\theta}) \geq (N/M)\bar{y}^* + \bar{r}' - g(\bar{r}', \underline{\theta}) \tag{18}$$

Constraints (15) and (16) are the participation constraints from relief organizations of type $\bar{\theta}$ and $\underline{\theta}$ respectively. Constraints (17) and (18) are the incentive compatibility constraints for the two types.

Proposition 3: In any separating equilibrium the low productivity type, $\underline{\theta}$, will choose $\underline{r}' = \underline{r}^* = \frac{\underline{\theta}}{2\mu}$.

Proof. Suppose not, and that $\underline{r}^*$ does not belong to the set of contributions that reveal $\underline{\theta}$ types. Then, it must be the case that it reveals $\bar{\theta}$ types. $\pi(r, \bar{y}, \underline{\theta}) > \pi(r, \underline{y}, \underline{\theta})$. Consequently, by equations (5) and (6), a $\underline{\theta}$ type would maximize his payoff by choosing $\underline{r}^*$ instead of $r' \neq \underline{r}^*$. But, because $\underline{r}^*$ signals a $\bar{\theta}$ type it contradicts the assumption of a separating equilibrium. □

Letting $\bar{r}' = \bar{r}^*$ and $\underline{r}' = \underline{r}^*$, and combining equations (17) and (18) yields the following condition (19), which if violated requires that the signal, if it is to separate, be sub-optimal from the standpoint of the relief organization.

$$(\underline{r}^* - \bar{r}^*) + g(\bar{r}^*, \bar{\theta}) - g(\underline{r}^*, \bar{\theta}) \leq (N/M)(\bar{y}^* - \underline{y}^*) \leq (\underline{r}^* - \bar{r}^*) + g(\bar{r}^*, \underline{\theta}) - g(\underline{r}^*, \underline{\theta}) \quad (19)$$

Proposition 4: If $\bar{r}^*$ and $\underline{r}^*$ satisfy equation (19) then there exists a separating equilibrium in efficient strategies.

Proof. Let $\bar{r}' = \bar{r}^*$ and $\underline{r}' = \underline{r}^*$, and rearrange (17) and (18) to look like (20) and (21). By definition, satisfaction of (17) and (18) yield a separation between $\underline{\theta}$ and $\bar{\theta}$ types.

$$(N/M)(\bar{y}^* - \underline{y}^*) \geq (\underline{r}^* - \bar{r}^*) + (g(\bar{r}^*, \bar{\theta}) - g(\underline{r}^*, \bar{\theta})) \quad (20)$$

$$(\underline{r}^* - \bar{r}^*) + (g(\bar{r}^*, \underline{\theta}) - g(\underline{r}^*, \underline{\theta})) \geq (N/M)(\bar{y}^* - \underline{y}^*) \quad (21)$$

Consequently, combining both conditions, yields, (19), which if satisfied by $\bar{r}^*$ and $\underline{r}^*$, producing a separation in optimal strategies, from an organizational standpoint. □

Of critical concern to the analysis of the separating equilibrium are the range of r values which are sustainable in a separating equilibrium. It was established in proposition 2 that any $\underline{\theta}$-type will provide $\underline{r}^* = \frac{\underline{\theta}}{2\mu}$ in a separating equilibrium. The question of what levels of relief are sustainable for $\bar{\theta}$-type organizations can be answered via an analysis of the situations in which a $\bar{\theta}$-type relief organization would not find it beneficial to provide the required signal for its type. The premise of the separating equilibrium is such that each relief organization finds it beneficial to signal their true productivity level via some action, where in this case the action is the provision of relief. As such, the lower bound, $r_{LBsepNM}$, on the set of separating signals must be the signal for which the $\underline{\theta}$-type relief organization is indifferent between pretending to be a $\bar{\theta}$-type or revealing itself to be a $\underline{\theta}$-type. The lower bound on the separating relief value is derived through satisfaction of the equality (22).

$$(N/M)\underline{y}^* + \underline{r}^* - \frac{\mu \underline{r}^{*2}}{\underline{\theta}} = (N/M)\bar{y}^* + r_{LBsepNM} - \frac{\mu r^2_{LBsepNM}}{\underline{\theta}} \tag{22}$$

Equation (22) characterizes the point at which the expected payoff, for a $\underline{\theta}$ organization, from providing the relief level consistent with its type is equal to the expected payoff consistent with pretending to be a higher type. $r_{LBsepNM}$ is the point which solves this equality, and is the lowest point beyond which a $\underline{\theta}$-type will always act as itself. This equality, $\mathrm{E}_{MN}[\pi(\underline{y}^*, \underline{r}^*, \underline{\theta})] = \mathrm{E}_{MN}[\pi(\bar{y}^*, r_{LBsepMN}, \underline{\theta})]$, is a quadratic, and can be solved as such. The solution to (22) consists of two roots, of which the positive root is taken, as relief is bounded in the positive quadrant. The separating relief level is dependent upon both the number of relief organizations and donors present, M and N respectively. Allowing that, $\underline{r}^* = \frac{\underline{\theta}}{2\mu}$, $r_{LBsepMN}$ can be written as in equation (23).

$$r_{LBsepMN} = \frac{\underline{\theta} + 2\sqrt{(\frac{N}{M})(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu}}{2\mu} \tag{23}$$

As a $\bar{\theta}$-type organization in a signaling game two options present themselves; 1) provide the necessary signaling level of relief and receive the expected payoff for an organization of $\bar{\theta}$-type, or 2) provide the optimal relief and risk being perceived as a $\underline{\theta}$-type and receiving the expected payoff level afforded those organizations. $r_{UBsepMN}$ represents the highest relief level that a $\bar{\theta}$ organization is willing to supply before it will choose not to comply and provide it's internal optimal level. As a consequence this upper bound $r_{UBsepMN}$ on the signaling equilibrium is found via satisfaction of equation (24), $\mathrm{E}_{MN}[\pi(\bar{y}^*, r_{UBsepMN}, \bar{\theta})] = \mathrm{E}_{MN}[\pi(\underline{y}^*, \bar{r}^*, \bar{\theta})]$, as show in equation (25).

$$(N/M)\bar{y}^* + r_{UBsep} - \frac{\mu r_{UBsep}^2}{\bar{\theta}} = (N/M)\underline{y}^* + \bar{r}^* - \frac{\mu \bar{r}^{*2}}{\bar{\theta}} \tag{24}$$

$$r_{UBsepMN} = \frac{\bar{\theta} + 2\sqrt{(\frac{N}{M})(\bar{y}^* - \underline{y}^*)\bar{\theta}\mu}}{2\mu} \tag{25}$$

Although all levels of relief between $r_{LBsepMN}$ and $r_{UBsepMN}$ are considered sustainable, the appendix on refinements justifies the choice of $r_{UBsepMN}$ as the signaling point of focus.

Proposition 4a: There exists a separating PBE equilibrium, that satisfies the following: (I)

$$r_j^*(\theta) = \begin{cases} \frac{\underline{\theta}}{2\mu} & \text{if } \theta = \underline{\theta} \\ r_{LBsepMN} & \text{if } \theta = \bar{\theta} \end{cases}$$

(II)

$$y_i^*(r_j) = \begin{cases} \underline{y} & \text{if } r_j \leq r_{LBsepMN} \\ \bar{y} & \text{if } r_j > r_{LBsepMN} \end{cases}$$

(III)

$$1 - \lambda(\theta | r_j) = Prob\{\theta = \underline{\theta} | r_j\}$$

$$\lambda(\theta|r_j) = Prob\{\theta = \bar{\theta}|r_j\} = \begin{cases} 1 & \text{if } r_j > r_{LBsepMN} \\ 0 & \text{if } r_j \leq r_{LBsepMN} \end{cases}$$

Proof. This result follows from proposition 2, equations (22),(5),(6), and signaling requirements 1 - 3. □

Proposition 5: There always exists a separating equilibrium in relief levels, such that $\bar{\theta}$-type organizations can distinguish themselves from $\underline{\theta}$-type organizations.

Proof. For a signaling equilibrium to exist, it must be the case that $r_{UBsepMN} > r_{LBsepMN}$. In order to eliminate the possibility of a separating equilibrium we must show that $r_{UBsepMN} < r_{LBsepMN}$ cannot hold. Below, we show by contradiction, that under the given parameter assumptions $r_{UBsepMN} < r_{LBsepMN}$ is ruled out, and consequently the possibility that there exists N such that no separating equilibrium exists, is also ruled out. Assume that $r_{UBsepMN} < r_{LBsepMN}$. Then, $(r_{UBsepMN} - r_{LBsepMN}) < 0$.

$$r_{UBsepMN} - r_{LBsepMN} = \frac{\bar{\theta} - \underline{\theta} + 2\sqrt{(\frac{N}{M})(\bar{y}^* - \underline{y}^*)\bar{\theta}\mu} - 2\sqrt{(\frac{N}{M})(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu}}{2\mu} \tag{26}$$

However, the expression (26) is negative, only if $\bar{\theta} < \underline{\theta}$, which is a contradiction of our original assumption. □

Figures (3) and (4) represent two scenarios in which separating equilibrium are present. Figure (3) outlines the instance in which $\bar{r}^* < r_{LBsepMN}$, making the separating relief point higher than the optimal level desired by the relief organization. Discussed in the refinements later on, the relief organization will provide $r_{LBsepMN}$ in this instance to separate. Figure (4) offers an alternative separating scenario, particularly one in which $\bar{r}^* > r_{LBsepMN}$. This instance allows the $\bar{\theta}$-type to provide it's optimal level $\bar{r}^*$ while simultaneously separating itself from $\underline{\theta}$-type relief organizations.

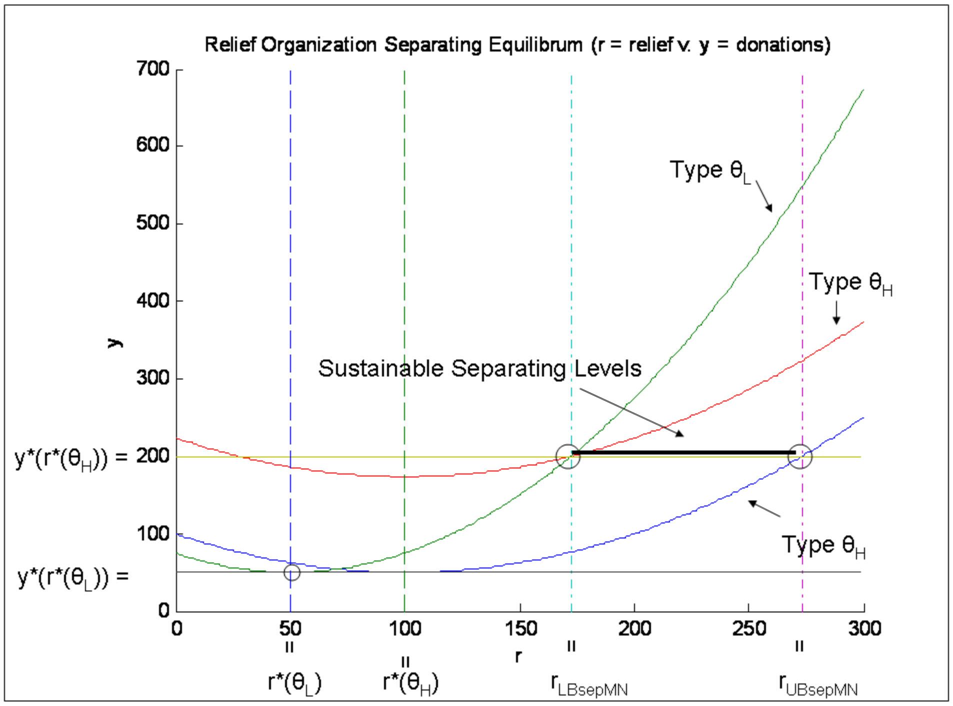

Figure 3: Separating Equilibrium: $\bar{r}^* < r_{LBsepMN}$

In addition to separating equilibrium, there also exist pooling equilibrium, the notion of which implies that the same relief level is provided by both high productivity and low productivity organizations, in equilibrium, at a particular relief site. Assume that $r^*(\bar{\theta}) = r^*(\underline{\theta}) = r^p$ where r^p is the pooling equilibrium level of relief provided, then the donor's beliefs about types remain unchanged. Consequently, in a pooling equilibrium, it must be that the donor provides $y^*(r^p) = \hat{y}^* = \lambda \bar{y}^* + (1-\lambda)\underline{y}^*$. With $\hat{y}^*$ as given, the last piece is the characterization of sustainable pooling levels of relief, r^p.

At the upper end of the possible pooling relief equilibrium levels is the relief level, r_{UBpMN}, that makes the the $\underline{\theta}$-type indifferent between providing its optimal relief level $\underline{r}^*$ at an expected payoff of $(N/M)\underline{y}^*$ and providing r_{UBpMN} and receiving the expected pooling payoff of $(N/M)\hat{y}^*$. This indifference can be represented via equation (27), and when solved yields, (28), of which the positive root is taken.

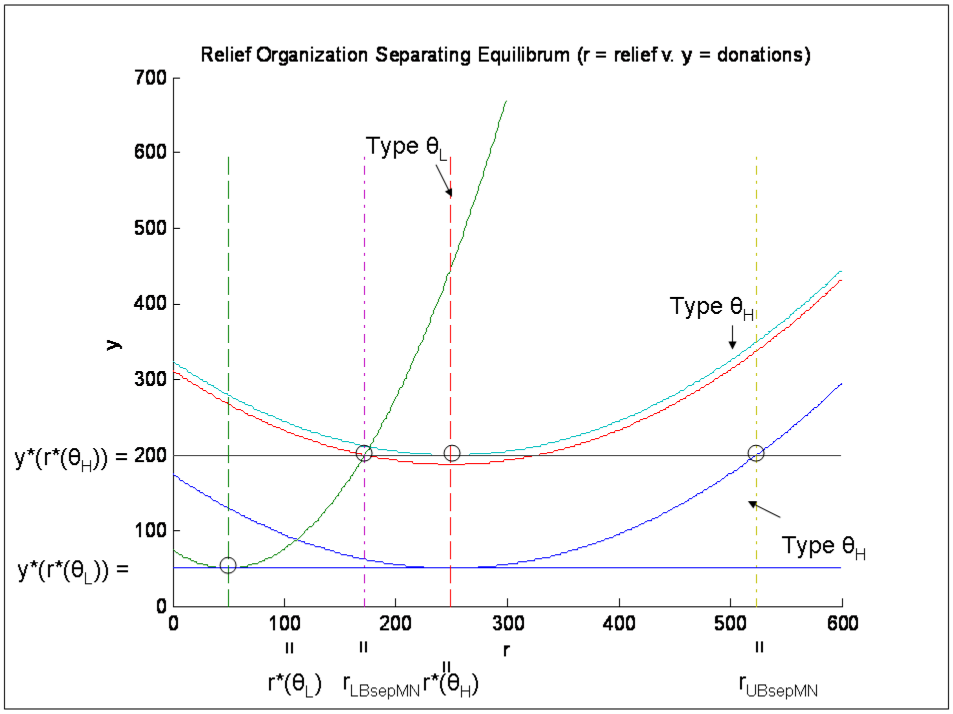

Figure 4: Separating Equilibrium: $\bar{r}^* > r_{LBsepMN}$

$$(N/M)\underline{y}^* + \underline{r}^* - \frac{\mu \underline{r}^{*2}}{\underline{\theta}} = (N/M)\hat{y}^* + r_{UBpMN} - \frac{\mu r_{UBpMN}^2}{\underline{\theta}} \tag{27}$$

$$r_{UBpMN} = \frac{\underline{\theta} \pm \sqrt{\underline{\theta}^2 - 4(\underline{r}^* + (\frac{N}{M})(-\hat{y}^* + \underline{y}^*))\underline{\theta}\mu + 4\underline{r}^{*2}\mu^2}}{2\mu} \tag{28}$$

Substitution for $\underline{r}^*$ and $\hat{y}^*$ yields:

$$r_{UBpMN} = \frac{\underline{\theta} + 2\sqrt{(\frac{N}{M})\underline{\theta}(\bar{y}^* - \underline{y}^*)\lambda\mu}}{2\mu} \tag{29}$$

The lower bound of the possible pooling relief equilibrium level is found via the relief level, r_{LBpMN}, which makes $\bar{\theta}$-type indifferent between providing its optimal relief level $\bar{r}^*$ at an expected payoff of $(N/M)\underline{y}^*$ and providing r_{LBpMN} and receiving the expected pooling payoff of $(N/M)\hat{y}^*$. This indifference is represented by equation (30). Solving the quadratic for r_{LBpMN} yields equation (31), of which the lower root is taken if positive, otherwise $r_{LBpMN} = 0$.

$$(N/M)\underline{y}^* + \bar{r}^* - \frac{\mu\bar{r^*}^2}{\bar{\theta}} = (N/M)\hat{y}^* + r_{LBpMN} - \frac{\mu r_{LBpMN}^2}{\bar{\theta}} \tag{30}$$

$$r_{LBpMN} = \frac{\bar{\theta} \pm \sqrt{\bar{\theta}^2 - 4(\bar{r^*} + (\frac{N}{M})(-\hat{y}^* + \underline{y}^*))\bar{\theta}\mu + 4\bar{r^*}^2\mu^2}}{2\mu} \tag{31}$$

Substitution for $\hat{r}^*$ and $\hat{y}^*$ yields:

$$r_{LBpMN} = \frac{\bar{\theta} - 2\sqrt{(\frac{N}{M})\bar{\theta}(\bar{y}^* - \underline{y}*)\lambda\mu}}{2\mu} \tag{32}$$

Proposition 5a: If there exists a pooling PBE equilibrium, it satisfies the following:

(I) Both types send the same message

$$r_p \in [r_{LBpMN}, r_{UBpMN}]$$

(II) Donor offers a donation based on *a priori* beliefs, such that,

$$y^*(r_j) = \hat{y}^* = \lambda\bar{y}^* + (1-\lambda)\underline{y}^*$$

for all $r_j \in [r_{LBpMN}, r_{UBpMN}]$.

(III) Beliefs about types remain unchanged, such that

$$Prob\{\theta = \bar{\theta}\} = \lambda, and Prob\{\theta = \underline{\theta}\} = 1 - \lambda$$

Proof. (I), (II), and (III) follow from the definition of pooling PBE. (I) is established via equations (29) and (31), (II) is a result of the assumed form of the donor's utility, and (III) follows. □

Figures (5) and (6) outline two pooling scenarios.

There are no sustainable levels of pooling equilibrium when $r_{LBpMN} > r_{UBpMN}$.

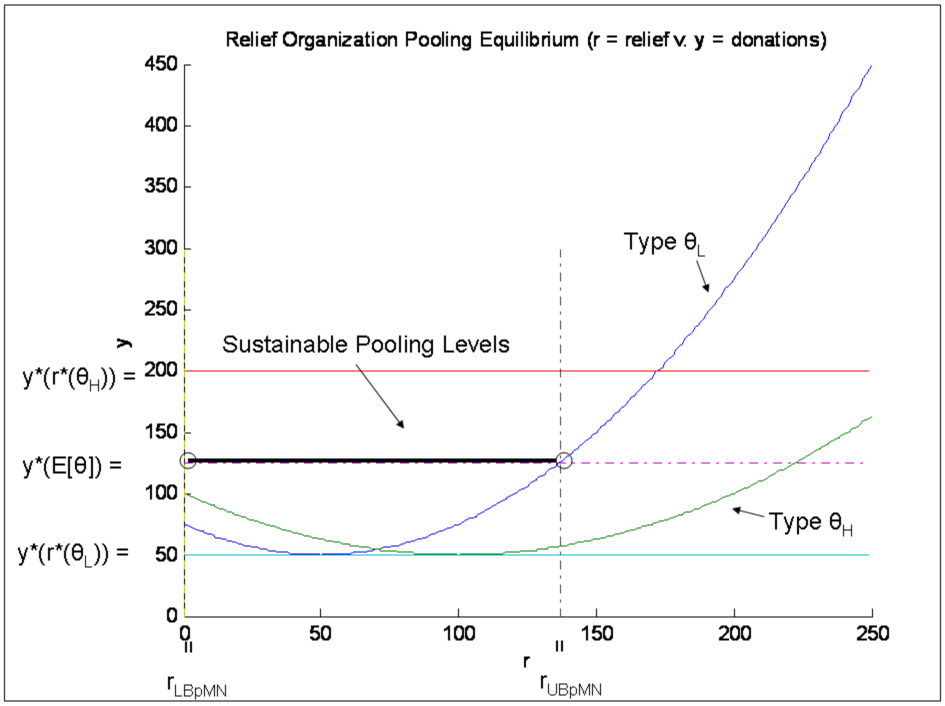

Figure 5: Sustainable Pooling Equilibrium Bounded at $r_{LBpMN} = 0$

2.3.5 Analysis

Taking the partial of equation (23) with respect to several variables of interest yields insight into how the lower bound on the separating condition responds to increases in the number of donors, the number of relief organizations, and the difference between the donation amounts, defined as $c = \bar{y}^* - \underline{y}^*$.

$$\frac{\partial r_{LBsepMN}}{\partial N} = \frac{\sqrt{\frac{N}{M}(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu}}{2N\mu} > 0 \tag{33}$$

$$\frac{\partial r_{LBsepMN}}{\partial M} = -\frac{\sqrt{\frac{N}{M}(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu}}{2M\mu} < 0 \tag{34}$$

$$\frac{\partial r_{LBsepMN}}{\partial c} = \frac{N\underline{\theta}}{2M\sqrt{\frac{cN\underline{\theta}\mu}{M}}} > 0 \tag{35}$$

Equations (33), (34), and (35) speak to the dynamics of the lower bound of the signaling equilibrium. In particular, insight into the effect of increased participation

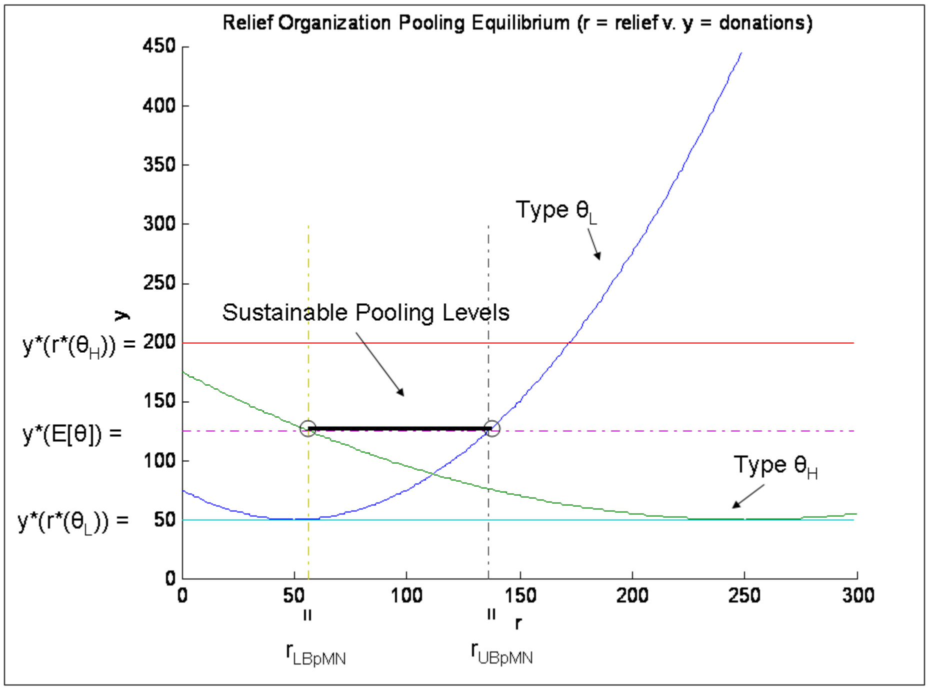

Figure 6: Sustainable Pooling Equilibrium Bounded $r_{LBpMN} > 0$

from the donor and relief organization perspectives. Equation (33) is positive for all $N > 0$, and shows that the lower bound on the separating level of relief is increasing in the number of donors interested in contributing to a relief area. However, the number of relief organizations has the opposite effect, as equation (34) is negative for all $M > 0$. As a consequence, the separating level, when greater than the organization's optimal level, is determined in part by the ratio $\frac{N}{M}$ of donors to relief organizations interested in an area. Equation (35) shows that as the spread, c, between the donation amount offered to high quality organizations ($\bar{y}^*$) and the amount to low quality organization ($\underline{y}^*$) increases, so does the relief level necessary to signal high quality.

2.3.5.1 Payoff Dominant Pooling Equilibrium

Given the initial inquisition into the impetus for congestion and competition, along with the characterization of the bounds on the separating equilibria and pooling equilibria a question of dominance arises. Specifically, whether or not there is a

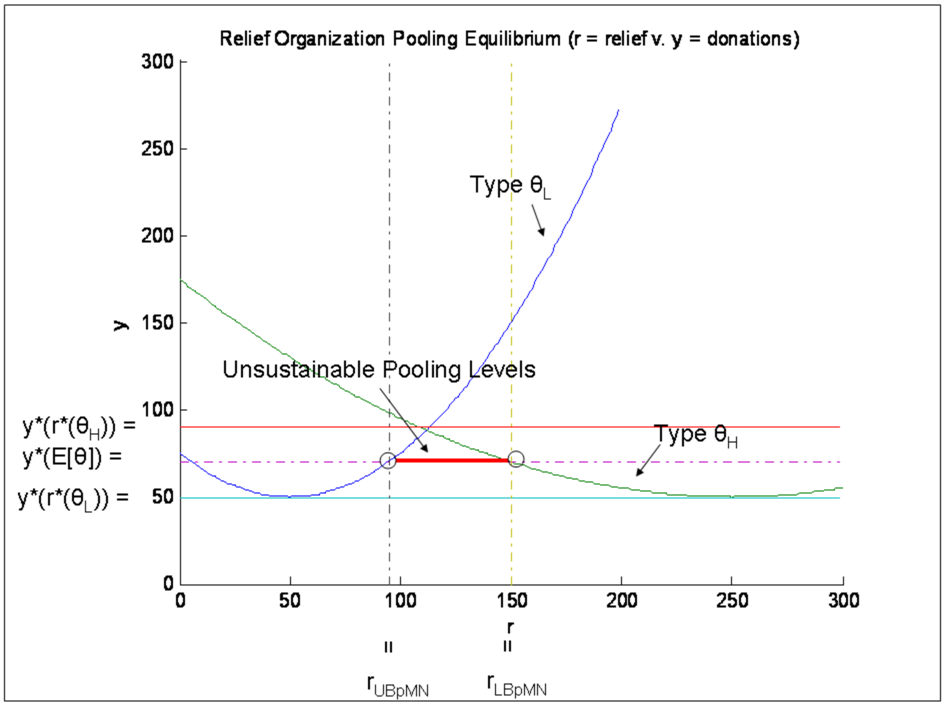

Figure 7: Unsustainable Pooling Equilibrium when $r_{UBpMN} < r_{LBpMN}$

combination of donors and relief organizations participating in a relief site that would yield an expected pooling equilibrium payoff that would dominate the expected payoff from separating for a $\bar{\theta}$ organization. Equation (36) represents the condition for dominance of the pooling equilibrium over the separating equilibrium, via indifference between the payoffs associated with the two. For a given separating level $r_{ParSepMN}$ the conditions on the existence of r_p that satisfy (36) are examined.

$$(\frac{N}{M})\hat{y}^* + r_p - \frac{\mu r_p^2}{\bar{\theta}} \geq (\frac{N}{M})\bar{y}^* + r_{ParSepMN}(M, N) - \frac{\mu r_{ParSepMN}^2}{\bar{\theta}} \qquad (36)$$

Proposition 6: A payoff dominant pooling equilibrium exists if 1) $r_{LBsepMN} \geq \bar{r}^*$, and if 2) $r_{LBsepMN} \geq r_{ParSepMN}$.

Proof. Condition (36) will not hold when $\bar{r}^* \geq r_{LBsepMN}$, with the reasoning following from the definition of $\bar{r}^*$. $\bar{r}^*$ is defined as the internal optimal level of relief that an organization wishes to provide to a specific area in a humanitarian crisis. If

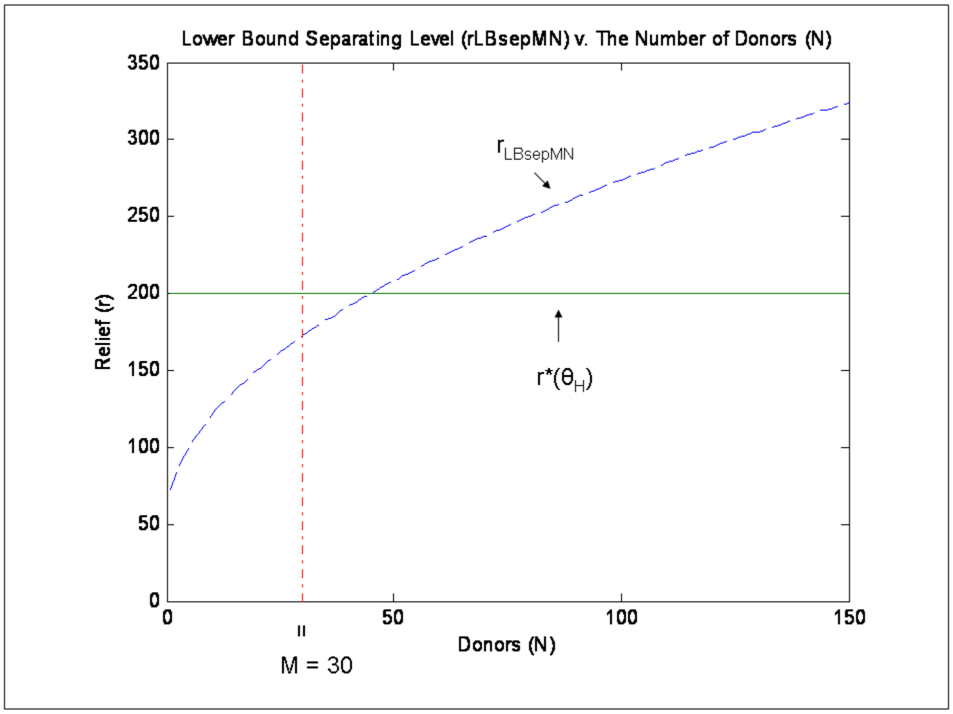

Figure 8: Donor (N) Dynamics: The response of the lower bound on the separating equilibrium in response to increases in donors.

$\bar{r}^* \geq r_{LBsepMN}$, then both $\bar{r}^*$ and $r_{LBsepMN}$ allow the organization to signal it's type. From the definition of $\bar{r}^*$ it follows that $\mathrm{E}_{MN}[\pi(\bar{y}^*, \bar{r}^*, \bar{\theta})] \geq \mathrm{E}_{MN}[\pi(\bar{y}^*, r_{LBsepMN}, \bar{\theta})]$. Consequently, if an organization is to signal it will be at the $\bar{r}^*$ level. Alternatively, we consider the option that the $\bar{\theta}$ type organization chooses to pool in this instance. If the organization pools on r_p it will receive a payoff $\mathrm{E}_{MN}[\pi(\hat{y}, r_p, \bar{\theta})]$. However, the following relation holds, for $\bar{r}^* \neq r_p$ such that: $\mathrm{E}_M N[\pi(\bar{y}^*, \bar{r}^*, \bar{\theta})] > \mathrm{E}_M N[\pi(\bar{y}^*, r_p, \bar{\theta})] > \mathrm{E}_M N[\pi(\hat{y}, r_p, \bar{\theta})]$. The relation shows that, when $\bar{r}^* \geq r_{LBsepMN}$ the organization will always prefer to signal at $\bar{r}^*$, affirming that there does not exist a dominant pooling equilibrium when $\bar{r}^* \geq r_{LBsepMN}$.

Substituting for $\bar{r}^* = \frac{\bar{\theta}}{2\mu}$ and solving (39) at equality for $r_{ParSepMN}$, yields the two roots (37) and (38), for which (38) is always positive. $r_{ParSepMN} = r_{ParSepMNpos}$ defines the point at which, given $r_p = \bar{r}^*$, Pareto dominance in a pooling equilibrium is asserted (i.e. assuming otherwise constant parameters, for any given (M, N)

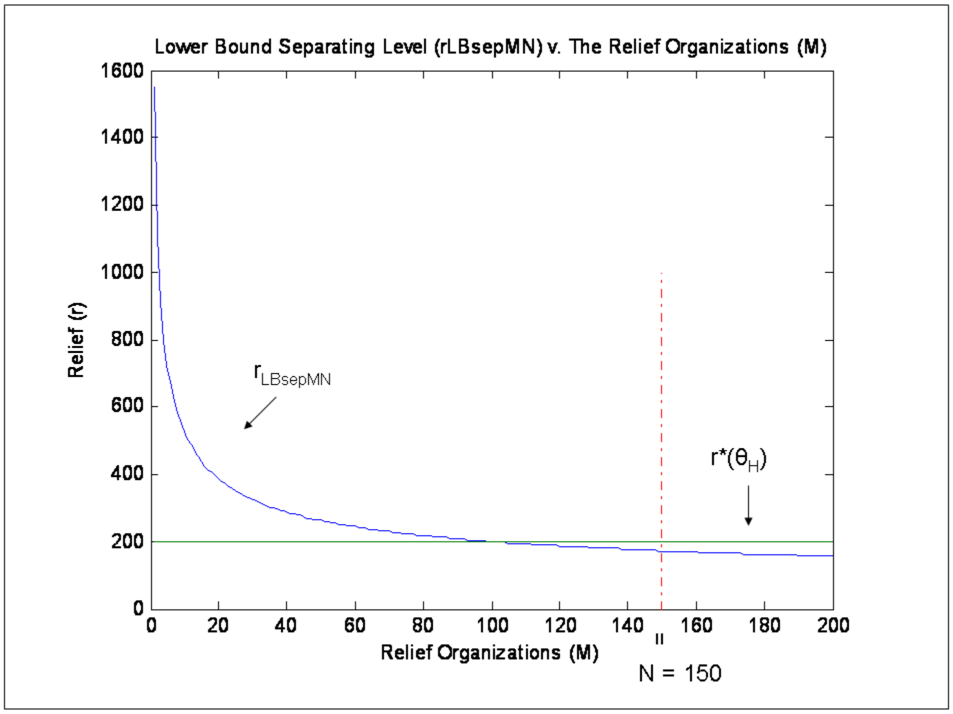

Figure 9: Relief Organization (M) Dynamics: The response of the lower bound on the separating equilibrium in response to increases in organizations.

pair, if $r_{LBsepMN}$ does not exceed $r_{ParSepMN}$ then there does not exist a dominant equilibrium).[13]

$$r_{ParSepMNneg} = \frac{M\bar{\theta}\mu - 2\sqrt{MN(\bar{y}^* - \hat{y})\bar{\theta}\mu^3}}{2M\mu^2} \tag{37}$$

$$r_{ParSepMNpos} = \frac{\bar{\theta}\mu + \frac{2\sqrt{MN(\bar{y}^* - \hat{y})\bar{\theta}\mu^3}}{M}}{2\mu^2} \tag{38}$$

Given the construction of (39), and concavity of the profit function, it must be the case that for $r_{LBsepMN} > r_{ParSepMN}$ and $r_{LBsepMN} \geq \bar{r}^*$, there exists a payoff dominant pooling equilibrium for $\bar{\theta}$ type organizations. □

[13] $r_{LBsepMN} \leq r_{ParSepMNneg}$ is also a condition under which a Pareto dominant pooling equilibrium may exist. However, this may occur in a very small instance of cases given the additional condition on the $\bar{r}^*$. Additionally, given the concavity of the objective function, an increase in donors will eventually violate this condition, whereas increases in donors beyond the positive root $r_{ParSepMNpos}$ will continue to satisfy the outlined condition.

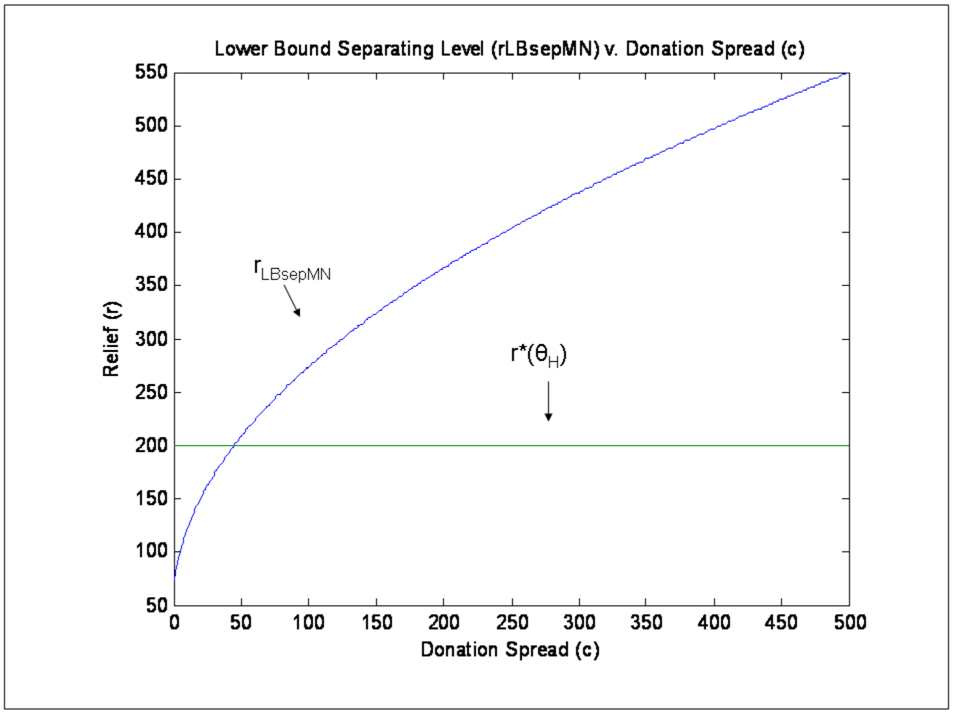

Figure 10: c Dynamics: The response of the lower bound on the separating equilibrium in response to increases in the spread between donation amounts for high and low type organizations.

Consider the range of pooling levels for which the condition (36) might hold. Equations (31) and (28) provide the range of feasible pooling levels, such that $r_p \in [r_{LBpMN}, r_{UBpMN}]$. Considering the question of whether or not condition (36) can be satisfied, $r_p = \bar{r}^*$ is taken to be the most likely candidate for $\bar{\theta}$-type organizations, as it yields the highest payoff for each expected donation level.

$$(\frac{N}{M})\hat{y}^* + \bar{r}^* - \frac{\mu \bar{r^*}^2}{\bar{\theta}} \geq (\frac{N}{M})\bar{y}^* + r_{ParSepMN} - \frac{\mu r^2_{ParSepMN}}{\bar{\theta}} \tag{39}$$

Given $r_{LBsepMN}$ and $r_{ParSepMN}$ consider whether $r_{LBsepMN} \geq r_{ParSepMN}$ can indeed hold in conjunction with $\bar{r}^* \leq r_{LBsepMN}$. If both conditions hold simultaneously then (40) and (41) should be positive simultaneously:

$$r_{LBsepMN} - \bar{r}^* = \frac{\underline{\theta} + \sqrt{\underline{\theta}^2 - 4(\underline{r^*} + Nq(-\bar{y}^* + \underline{y}^*))\underline{\theta}\mu + 4\underline{r}^{*2}\mu^2}}{2\mu} - \frac{\bar{\theta}}{2\mu} \quad (40)$$

$$r_{LBsepMN} - r_{ParSepMN} = \frac{\underline{\theta} + \sqrt{\underline{\theta}^2 - 4(\underline{r^*} + Nq(-\bar{y}^* + \underline{y}^*))\underline{\theta}\mu + 4\underline{r}^{*2}\mu^2}}{2\mu} - \frac{\bar{\theta}\mu + \frac{2\sqrt{MN(\bar{y}^* - \hat{y})\bar{\theta}\mu^3}}{M}}{2\mu^2} \quad (41)$$

Which reduce to:

$$r_{LBsepMN} - \bar{r}^* = \frac{\underline{\theta} - \bar{\theta} + 2\sqrt{\frac{N(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu)}{M}}}{2\mu} \quad (42)$$

$$r_{LBsepMN} - r_{ParSepMN} = \frac{-2\sqrt{MN(\bar{y}^* - \hat{y}^*)\bar{\theta}\mu^3} + M\mu(\underline{\theta} - \bar{\theta} + 2\sqrt{\frac{N(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu)}{M}})}{2M\mu^2} \quad (43)$$

Letting N_1^I,N_2^{Ip}, and N_1^{In} represent the donor levels which satisfy $r_{LBsepMN} - \bar{r}^* = 0$ and $r_{LBsepMN} - r_{ParSepMN} = 0$, respectively, allows solutions for each indifference point, if it exists, for the given parameter set.

$$N_1^I = \frac{M(\bar{\theta} - \underline{\theta})^2}{4(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu} \quad (44)$$

$$N_2^{Ip} = \frac{-M(\bar{\theta} - \underline{\theta})^2(\hat{y}^*\bar{\theta} + \underline{y}^*\underline{\theta} - \bar{y}^*(\bar{\theta} + \underline{\theta}))\mu + \sqrt{-M^2(\hat{y}^* - \bar{y}^*)(\bar{y}^* - \underline{y}^*)\bar{\theta}(\bar{\theta} - \underline{\theta})^4\underline{\theta}\mu^2}}{4(\hat{y}^*\bar{\theta} - \underline{y}^*\underline{\theta} + \bar{y}^*(\underline{\theta} - \bar{\theta}))^2\mu^2} \quad (45)$$

$$N_2^{In} = \frac{-(M(\bar{\theta} - \underline{\theta})^2(\hat{y}^*\bar{\theta} + \underline{y}^*\underline{\theta} - \bar{y}^*(\bar{\theta} + \underline{\theta}))\mu + \sqrt{-M^2(\hat{y}^* - \bar{y}^*)(\bar{y}^* - \underline{y}^*)\bar{\theta}(\bar{\theta} - \underline{\theta})^4\underline{\theta}\mu^2})}{4(\hat{y}^*\bar{\theta} - \underline{y}^*\underline{\theta} + \bar{y}^*(\underline{\theta} - \bar{\theta}))^2\mu^2} \quad (46)$$

Figure (11) outlines a scenario where for given M, there exists a dominant pooling

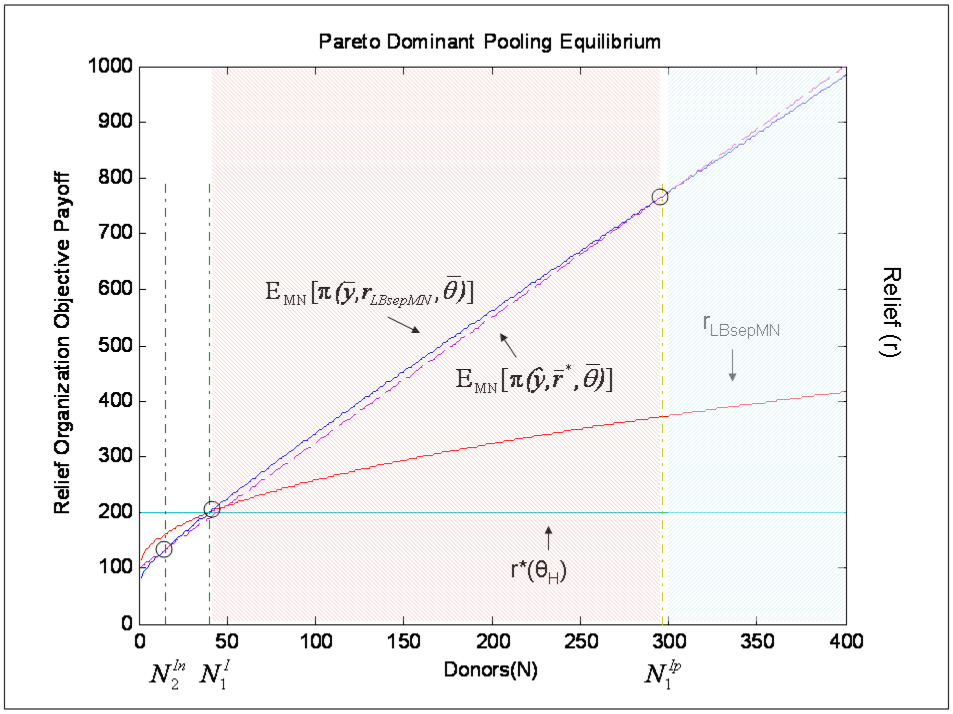

Figure 11: Payoff Dominant Pooling Equilibrium at Pooling Level $r_p = \bar{r}^*$

equilibrium beyond N_2^{Ip}. Beyond N_1^I, the condition $r_{LBsepMN} \geq \bar{r}^*$ is satisfied, and beyond N_2^{Ip} the condition $r_{LBsepMN} \geq r_{ParSepMN}$ is satisfied.

The paper begins with an initial assumption that it is always optimal for $\bar{\theta}$ relief organizations to signal their type, and not allow pooling by lesser organizations. However, the results presented here suggest that there may be instances in which it is not always optimal for $\bar{\theta}$ organizations to actively signal their type. Such environments present an opportunity for lesser quality organizations to pool with higher productivity organizations. The discussion considers whether there are real world analogs to the pooling environment suggested here, and what they mean. Of particular interest, is whether or not there is always a point at which the pooling equilibrium becomes Pareto dominant. Proposition (7) says that λ must be of a certain value if a dominant pooling equilibrium is to exist.

Proposition 7: It is not the case that there exists a payoff dominant pooling equilibrium when $\lambda \leq \frac{\bar{\theta}-\underline{\theta}}{\bar{\theta}}$.

Proof. Take the denominator of (45), $4(\hat{y}^*\bar{\theta} - \underline{y}^*\underline{\theta} + \bar{y}^*(\underline{\theta} - \bar{\theta}))^2\mu^2$. If

$$4(\hat{y}^*\bar{\theta} - \underline{y}^*\underline{\theta} + \bar{y}^*(\underline{\theta} - \bar{\theta}))^2\mu^2 \leq 0, \tag{47}$$

then $N_2^{Ip} < 0$, which means that there does not exist a positive N that satisfies $r_{LBsepMN} - r_{ParSepMN} = 0$. Solving for λ yields the condition,

$$\lambda \leq \frac{\bar{\theta} - \underline{\theta}}{\bar{\theta}} \tag{48}$$

Where, for any λ satisfying (48), there does not exist a payoff dominant pooling equilibrium. □

How this, and the preceding analysis relates to the problems considered in section (2.2) is considered more formally below.

2.4 Interpreting Relief Response Through the Lens of "Signaling in Relief"

In the previous sections we were able to define a simple game of the dynamics between relief organizations and donors, along with both pooling and separating equilibrium to describe the behavior of organizations in response to the assumed behavior of donors. Here, we consider how this analysis might inform the competitive behavioral phenomena among relief organizations associated with the waste, congestion, and aversion to coordination discussed at the outset. In particular there are two behaviors of interest; 1). the behavior of the separating equilibrium in response to environment conditions, and 2). when can a pooling equilibrium be expected to occur, and what does it mean.

Returning to the dynamics defined in equations (33), (34), and (35), we consider how these might be used to analyze organization behavior. (33) and (34) show N and

M to have opposite effects on the required separating level of relief. As a consequence the ratio $\frac{N}{M}$ is informative, as the smaller the ratio, the smaller the separating level required, and vice versa. As N increases the opportunity for expected donations increases, while if M increases so does the competition level within an area . In relation to areas of humanitarian relief, in particular those of high attention, N and M are both likely to increase. How they increase, and the point at which they stabilize will help define the composition of a particular area as it regards organization behavior. The model assumes a static state of donors and organizations in an area, but in practice both should be expected to evolve at varying rates. In particular, because of the high number of organizations found in high attention relief areas, one might infer that individual organizations internalize the effects of an anticipated increase in donors, before the effects of competition are internalized. Once competition is internalized one would expect to see a reduction in the number of organizations associated with an area, or at the very least a lessening in the publicity seeking behavior as defined by excessive signaling. This can in part be used to explain why development work, post-emergency phase, is often carried out by a much smaller subset of organizations.

The dynamic implied by (35) of the spread between donations to $\bar{\theta}$ and $\underline{\theta}$ is rather intuitive, as it implies that the greater the reward for being seeing as high quality organization, the more desirable it would be for each organization to be seen as such. This dynamic is not very illuminating in the context of high publicity relief areas, but once considered across the landscape of potential humanitarian causes it can be more informative. In particular, if one considers that there are some areas in which the difference in quality of the organization is not perceived to matter as much then there is not as large an incentive for organizations to signal their type beyond what they would normally provide to an area.

Proposition 5a establishes the conditions for the existence of a pooling equilibrium, whereas proposition 7 defines instances in which one might be dominate the separating payoff for a $\bar{\theta}$ organization. What proposition 7 says, is that given the relative productivity levels of $\bar{\theta}$ and $\underline{\theta}$ type organizations, there exists a threshold level for λ beyond which the pooling equilibrium becomes dominant. Thus, for areas in which the belief about the quality of the organizations that participate there is high enough, $\bar{\theta}$ type organizations would not find it beneficial to try to distinguish themselves from $\underline{\theta}$ organizations. This however, would allow lesser quality organizations to signal at the high quality level, and effectively capture a larger portion of potential donations. This result can in part be used to explain why high attention relief areas are more prone to congestion and competition, both at the level of resource allocation, and at the participation level.

At the resource level, while $\bar{\theta}$ organizations are not compelled to provide beyond their optimal level, lesser organizations are, with the expectation of higher future donations. While the analysis has occurred through the consideration of relief as being monetary, it is important to note that in practice the way that increased relief occurs can be through other avenues, such an increase in the labor supply, or increased visibility via strategic positioning. In this sense, while not necessarily beneficial to the relief effort, lesser type organizations have a distinct motivation to participate in this behavior within areas for which λ is high. Given this, it is important to consider when λ might be high. If one considers, as in the beginning that λ is a measure of the donor's beliefs about the quality of the organizations participating in an area, then it is not a stretch to infer that high attention relief areas might be precisely the kind of area for which donors have higher beliefs about the quality of the organization participating there.

Furthermore, while the dynamics of organization decision making as it regards selection into particular areas is not modeled, it is not hard to imagine that lower quality organizations would find high λ areas more desirable, causing an influx of organizations to areas with this characteristic, further explaining issues of congestion within a given site. Further analysis is considered below, in which a production function for the relief site is assumed, so that organization behavior can be considered in a more holistic context.

2.4.1 Welfare Analysis

While the utility of affected populations in the relief space has yet to be modeled, it is undoubtly the end goal of both the donor and the relief organization to improve the conditions of the affected populations. The question of welfare, and welfare improvement can be considered via the aggregation of three perspectives, namely the donors, relief organizations, and the affected populations.

Framing the original problem as a signaling game between the donors and relief organizations obscures, to some extent, the original focus on congestion, waste and coordination in relief efforts, as has the selection of the objective function. What has been shown to this point has specifically focused on the signaling equilibria between the donor and humanitarian relief organizations. This is an important step in understanding the behaviors of relief organizations, specifically in the context of donors. While there has yet to be an explicit connection between organizational behavior and the realities of the relief needed on the ground, this initial analysis paves the way for such a connection to be made, and allows for understanding of the tradeoffs between the dual motives.

Also left to be shown is how the organization's optimal relief level can be related in any meaningful way to the needs of the relief area, and not just from the isolated perspective of an organization. The impetus for this chapter was motivated out of an analysis of congestion and waste in these relief areas, as a result of competition for donations. It has been shown that a consideration of dual motives in a signaling context may cause the relief organization to provide more resources than they would in optimality. While an interesting result, optimality is not particularly meaningful at this point, as it does not have an overt connection to the relief being provided by other organizations, nor to the relief requirements on the ground.

In the introduction of the relief organization payoff function a scalar parameter μ, on the cost function, was introduced as a representation of the utility a relief organization receives from actually providing the relief. The use of this parameter can be extended by allowing that μ is dependent on the relief site k, and is not only reflective of a particular organization's affinity for that type of work, but also reflective of the level of response needed. As such, by allowing μ to be a representation of the necessary relief at a particular site one can forge a connection between the relief required on the ground, and the importance that it takes on within the objective function of the relief organization.

Assuming homogeneous organizations, μ can be indexed for each relief site, such that μ_k is reflective of the necessary relief at a disaster area k. As noted previously $\mu_k \in (0, \infty)$ appears in the cost function $g_k(r, \theta) = \frac{\mu_k r^2}{\theta}$. Consequently, there is an inverse relationship between μ_k and the importance afforded a particular relief site, with $g_k(r, \theta)$ increasing in μ_k, and $r^* = \frac{\theta}{2\mu_k}$ decreasing in μ_k (i.e. the smaller μ_k the greater the need for relief at a site). As such, it might be said that a densely populated area recently hit by a hurricane may have a much smaller μ value than a rural area hit by a tornado. While both scenarios are of importance, the former would clearly merit a more sustained relief effort both in terms of time and resources committed.

The last piece to this puzzle is a production function for the relief site that describes how the assistance provided by the various organizations actually impacts conditions on the ground. This allows aggregation of the total relief across all organizations, providing a better understanding of how signaling can impact the total relief level at a site. Take a simple function $V : \Re^M \rightarrow \{0, 1\}$, as an indicator function denoting whether or not enough relief has been provided in the current period. Taking $r_k^{total} = \sum_{j=1}^{M} r_{jk}$ as the total amount of assistance provided by all relief organizations to area k, and set r^{thres} as the relief threshold, one can define V as follows:

$$V(r^{total}) = \begin{cases} 1 & \text{if } r^{total} \geq r^{thres} \\ \\ 0 & \text{if } r^{total} < r^{thres} \end{cases} \tag{49}$$

Using V as an indicator of whether or not the necessary relief has been provided in a particular area allows for a rough quantification of the effects of signaling on the amount of aid received by an area in need. Based on the results developed from the signaling model, the effects presented here are intuitive. However, the presentation of the indicator function allows the previous results to be placed in a more accessible context.

Not explicitly noted earlier, but an important difference between the presented signaling model and the canonical signaling model of the labor market is that as more firms enter the labor market, it has no effect on the expected wage of the laborer. In fact, more firms in the labor market actually help to drive the wage to the competitive wage rate, equal to the expected output of the worker. Consequently the presence of additional firms, above two, does not effect the signaling equilibrium that is found in that model. However, in the presented model, the presence of additional donors, which takes the place of the firm in the labor market example, alters the signaling equilibrium in a significant way. Most notably, the presence of a large number of donors forces high productivity organizations to provide more relief to signal their quality than when there is a lesser amount of donors. Dependent on the situation this may or may not be desirable. With respect to the relief organizations there are three states in which they can find themselves as it defines their giving to a particular relief area, all of which are relative to their internally defined *optimal* relief levels.

These conditions include, under provision, provision at optimum, and over provision. Removing these states from the context of the relief organization interests, and placing them in a larger framework one may find that depending on the *humanitarian context* each of these states could possibly be desirable.[14]

Given $V_k(r^{total})$ for a relief area k and $V_k(r^{total}) \neq 1$, it may in fact be desirable that organizations be induced to over provide in a separating equilibrium. As has been shown in the preceding analysis, depending on the mix of donors and relief organizations in a particular area, the organizations may be forced to provide more than they might like, but when compared with what is needed on the ground, it in fact might not be enough. Meanwhile, signaling moves these organizations to provide more than they would in a non-signaling environment, and goes toward alleviating the need at the relief site.

Take the scenario where no signaling is allowed and $V_k(r^{total}) = 0$, but where $r_k^{total} = \sum_{j=1}^{M} r_{jk} = r_k^{thres} - \epsilon$. This suggests, given the appropriate humanitarian context, and the ability to signal there may exist a signaling equilibrium, in which the participating $\bar{\theta}$-type organizations are all induced to give $r_{jk} + \frac{\epsilon}{M_{\bar{\theta}}}$, thereby allowing for $r_k^{total} = r_k^{thres}$, which now turns the indicator $V_k(r^{total})$ to 1.[15] In this situation the over provision induced by signaling becomes a good thing from the standpoint of the relief area. However, one can just as easily imagine a situation in which the over provision is unnecessary and only leads to wasted resources at the site of interest. Having established $V_k(r^{total})$ as the production function at the site level, it is now possible to define the overall welfare in a generic manner via aggregation of donor utility, relief organization payoff, and population relief, as in equation (50). α_1, α_2, and α_3 are weights on the donor, relief organization, and population utilities, respectively. This,

[14]Taking welfare, utility, and payoff functions as static, the humanitarian context consists, in a loose sense, of a pair that defines the number of donors and relief organizations participating in a relief site. Define the humanitarian context of a relief area k, via $\{N, M\}_k$.

[15]$M_{\bar{\theta}}$ is defined as the number of $\bar{\theta}$-type relief organizations in the system, and $M_{\underline{\theta}}$ as the number of $\underline{\theta}$-types

characterization is slightly deceiving, in that it fails to account for the negative effects of waste in a particular area. Waste can be quantified as in equation (51). A positive value of the waste variable denotes overprovision, and negative values denote a deficit in relief for a given area.

$$W(U_1(y_1),\ldots,U_N(y_N),\pi_1(r_1),\ldots,\pi_M(r_M),V(r^{total})) \\ = \alpha_1 \sum_{i=1}^{N} U(y_i) + \alpha_2 \sum_{j=1}^{M} \pi(r_j) + \alpha_3 V(r^{total}) \tag{50}$$

$$Waste = \sum_{j=1}^{M} r_{jk} - r_k^{thres} \tag{51}$$

Below,R_{NS}^{TOT} and R_S^{TOT} are defined such that they represent the total amount of relief provided to an area in the non-signaling and signaling cases respectively.

$$R_{NS}^{TOT} = M_{\underline{\theta}}\underline{r}^* + M_{\bar{\theta}}\bar{r}^* \tag{52}$$

$$R_{S}^{TOT} = M_{\underline{\theta}}\underline{r}^* + M_{\bar{\theta}} r_{LBsepMN} \tag{53}$$

Using R_{NS}^{TOT} and R_S^{TOT} the measure of waste can be defined for the non-signaling and signaling cases.

$$Waste_{NS}^{TOT} = R_{NS}^{TOT} - r_k^{thres} \tag{54}$$

$$Waste_{S}^{TOT} = R_{S}^{TOT} - r_k^{thres} \tag{55}$$

Proposition 8: Given a $\{M, N\}$ context, the presence of signaling will never cause there to be less resources available in an area when contrasted with the outcome in the non-signaling environment.

Proof. Given M, let $M_{\underline{\theta}}$ and $M_{\bar{\theta}}$ denote the number of $\underline{\theta}$ type and $\bar{\theta}$ type organizations, respectively, such that $M = M_{\underline{\theta}} + M_{\bar{\theta}}$. In a no signaling situation, the total amount of relief provided to an area can be defined by R_{NS}^{TOT}, where each type provides their optimal relief level, $\underline{r}^*$ and $\bar{\theta}^*$. R_S^{TOT} is the total amount of relief provided in an environment in which signaling is allowed. If $R_S^{TOT} \geq R_{NS}^{TOT}$, then it must be the case that $M_{\bar{\theta}} r_{LBsepMN} \geq M_{\bar{\theta}} \bar{r}^*$.

To show that $M_{\bar{\theta}} r_{LBsepMN} \geq M_{\bar{\theta}} \bar{r}^*$ consider that the lower bound on signaling, $r_{LBsepMN}$ will fall into one of three categories, (1) $r_{LBsepMN} > \bar{r}^*$, (2) $r_{LBsepMN} < \bar{r}^*$, or (3) $r_{LBsepMN} = \bar{r}^*$. Working from the assumption that through refinements the donor chooses the utility maximizing level of relief, then in case (1) the donor will signal at $r_{LBsepMN}$ making $M_{\bar{\theta}} r_{LBsepMN} > M_{\bar{\theta}} \bar{r}^*$. In case (2) the donor can separate by signaling at his utility maximizing level, and will do so, causing $M_{\bar{\theta}} r_{LBsepMN} = M_{\bar{\theta}} \bar{r}^*$. Similarly case (3) leads to $M_{\bar{\theta}} r_{LBsepMN} = M_{\bar{\theta}} \bar{r}^*$.

Conversely, consider the possibility of a pooling equilibrium. It was established in proposition 6, that a payoff dominant pooling equilibrium can occur, under certain conditions, at a pooling level of $\bar{r}^*$. In this instance, the total relief provided in an area can be defined via R_{pool}^{TOT}, as defined below.

$$R_{pool}^{TOT} = M_{\underline{\theta}} \bar{r}^* + M_{\bar{\theta}} \bar{r}^* \tag{56}$$

Because $\bar{\theta} > \underline{\theta}$ and $\bar{r}^* > \underline{r}^*$, then $M_{\underline{\theta}} \bar{r}^* > M_{\underline{\theta}} \underline{r}^*$. Thus, $R_{pool}^{TOT} > R_{NS}^{TOT}$ $\square$

2.4.2 Policy

The model has several policy implications as it regards facilitating better coordination and resource distribution in the humanitarian relief sector. Specifically, we have shown that signaling can lead to two types of congestion effects. Congestion in resources as shown through the separating equilibrium, and congestion in organizations as implied through the Pareto dominant pooling equilibrium. The need to signal is manifested out of the informational asymmetries that exist within the humanitarian marketplace. As a consequence of the results following from the signaling structure, it is clear that an environment in which types are observable allows for more discretion as it regards placement of resources, and the level of resources provided, from an organization standpoint. This leads to consideration of the central question, of how one might put structures or policies in place to drive the current environment toward one where signals are not necessary, or at the very least are not as palpable. Ways in which the power of signals can either be reduced or eliminated are considered below.

One of the prevailing policy remedies for signaling markets, in which inefficiency is created from actors' desire to distinguish themselves in some fashion, is that of *cross-subsidization*. In effect, cross-subsidization is exercised through a central authority with the power to determine behavior via incentive alignment as controlled through resource distribution. In this instance, given the lack of a centralized authority within the humanitarian domain, specifically one with carte blanche over funds, it is important to consider how such an organization might operate as it regards subsidization and behavior. In part, the authority's incentive structure will vary dependent upon the type of equilibrium situation they are dealing with, and thus it helps to have previously characterized the parameters which could lead to either a signaling or a pooling equilibrium, and what type of investment the authority could expect to see in both situations. However, in both situations the underlying problem is how does one control access to what is essentially a public good.

In the separating occurrence, beyond a certain point, there are presumably high productivity organizations which over provide, and low productivity organizations that provide at their optimum. When viewed with respect to the amount of relief necessary for a particular situation the aggregate provision may indeed by necessary. However, if the provision level is not necessary, a central authority with discretion over funds could implement a scheme in which those organizations who signal their type at the appropriate level receive their expected funds, and those organizations which cannot provide at the separating level are given a subsidy, or grant, to invest their resources in another area. Such a grant, would have to be comprised of an amount that would make the low productivity organization indifferent between investment in either area. As a result, not only is investment in other causes or areas fostered, but the effects of congestion and overprovision are mitigated at the initial site of interest, making coordination an easier prospect.[16]

In the pooling occurrence the scheme gets a bit more complicated. In the separating case, high productivity organizations had a natural inclination to separate via provision at a certain level. In the instance of pooling, these organizations are content with providing at their optimal level and allowing lower productivity organizations to pool on this level. Although we do not model the dynamics of the equilibrium over time, it would presumably not be a stretch to infer that pooling environments would encourage increased participation from low type organizations as time advanced. Accepting this premise, the increased participation of these organizations would cause wasted resources and coordination difficulties as their numbers increased. Consequently, the problem of how one limits access persists, but in a slightly different context. One solution to this problem, in the spirit of subsidization, would be to encourage highly productive organizations to signal at the separating level, and provide a grant to make up for their payoff loss from not pooling. While this accomplishes the goal of distinguishing between organizations, the authority is then forced into the separating contingency, in which the authority would once again have to incentivize low type organizations to stay away, if that is what is necessary. Behavior can be altered through grants and lump-sum payments, but the pool of funds may not support realignments through this process, and forcing organizations to over provide for the sake of separation may be counter-productive. A potential remedy to this problem, would be forcing the organizations to provide another costly signal of capability and

[16]Issues of timing may need to be considered, in that these funds may need to be allocated up front, but recouped on the back end. In this sense such an organization would act as revolving fund.

preparedness beforehand, such that organizations could be classified based on readiness. Through this tiered system, although organizations could still pool on resource provision, the pooling could be broken through the capability requirements, which would then allow a central authority to make better decisions about who is needed where and how best to allocate funds to accomplish that, in a less costly manner.

In a more straight forward fashion, if there were a central authority that did not have funds to incentivize organizations, but simply had control over where organizations could and could not go and what they could do when they got there as it concerns division of labor, there would still be effects on the strength of the relief signal. In this sense, this structure shifts the power in signaling from how much relief was provided, and where, to how well did an organization fulfill its requested assignment. If donors are aware of this structure, relief as a signal no longer has much meaning, as the provision requests were made from outside the organization. While bringing a centralized command structure to what is a highly de-centralized system is a preferred solution, the practicality of implementation is inhibited by logistical considerations, and to a large extent incentives. There are individual foundations and governments which are large enough to leverage a certain amount of control over the organizations to which they contribute. However, these foundations and governments are themselves spread out, and have varying agendas. The only way in which a centralized structure could become feasible is through the concentration of funding sources. If donors trust one foundation above all others as being good stewards of their funds, and come to recognize that this foundation has the sufficient skill and knowledge to best utilize these funds, then organizations, and particularly smaller ones, will become reliant on this foundation for funding. Chapter 4 consides a variation of this and shows to one extent how the power of signals may lose some of their effect when considered in the context of a trustworthy governing institution.

Beyond consideration of a central authority, it is also worthwhile to consider the power of outside organizations to influence behavior. In this instance how these entities might help to reduce the power of relief as a signal via diversification of the available signals is considered. Mentioned in the introduction is the notion that relief organizations were unique with respect to other charitable organizations in the sense that the number of types of credible signals which they have available for use is smaller than that of other charitable organizations. If there are independent organizations which can be created, and there are some which currently exist, to document and ascertain effectiveness beyond use of funds via Form 990 analysis, then ways in which organizations can credibly tell others that they are high quality organizations can be increased. However, even beyond the transformational policy recommendations, it is important that funding organizations stress the importance of cooperation and coordination via existing grants.

2.5 Conclusions and Extensions

As outlined in the introduction, this work seeks to build a foundational model from which the effect of information on the behavior of donors and relief organizations within the humanitarian relief marketplace can begin to be quantified and better understood. The model provides some curious insights into these dynamics via the characterization of separating and pooling equilibrium, under an assumed dynamic structure, and additionally provides some context for when one might expect to see either occur. What can be definitively said, is that information and the need to convey it as manifested through signaling, alters organizational behavior in the provision increasing direction, such that each organization will at minimum contribute what they would in the perfect information setting, but in fact may contribute more than they would to the public good with full information in hand. While it can be speculated that these behavior alterations obstruct the completion of the primary mission, it will require empirical analysis to make definitive conjectures along these lines. The presented model builds upon the traditional models of signaling, and offers several extensions to satisfy the distinct nature of the considered problem.

The primary extension of the model deals with the altruistic foundations on which relief organizations are derived. The most easily relatable signaling model is that of Spence's model of the job market in which education is used as a signal to employers of a worker's true type. In a perfect information environment, workers of both types will choose not to obtain any education at all. Only when there is uncertainty about types will a high productivity worker choose to obtain education. However, in the instance of relief organizations, regardless of type and the information environment, these organizations will always choose to provide some level of relief. The organization, in this sense akin to workers, will always find fulfillment in providing some level of relief as it allows for progress toward completion of their core mission, even if the relief does not lead to any future donations. This provision leads to a slightly more complicated equilibrium structure, particularly as it concerns refinements, and the focus on which equilibrium will occur in practice.

Another deviation occurs in the consideration of how wages, or donations, are derived within this model. Donors, which are considered to be a direct parallel of the firms in the labor market model, are looking to provide a donation to relief organizations much as firms provide a wage to workers. However, in the instance of firms, the wage that is provided to workers can be explained through satisfaction of a competitive market equilibrium, in that no firm would provide a wage greater than the expected productivity, but neither would any firm provide a wage below this level, lest it price itself out of the market for any workers. In the presented model, the donation levels of donors are not derived from a competitive market, but from altruistic inclinations, in the sense that each individual has some willingness or desire to give part of their wealth to a public cause or good. This model leverages the previous work on altruistic giving to define standard levels of giving outside of the competitive environment.

Lastly, the model was developed with the notion of competition as a driver of relief organization behavior. Consequently, some may find it curious that the model does not directly consider competition within the organization objective function, as one might expect, via a congestion term. However, competition is inherently present within the model in two senses; 1). competition between low productivity and high productivity types, which was the impetus for the model, and 2). competition between individual organizations as proxied through the use of expectation in determining potential payoffs to each organization. Both dynamics enter directly into the characterization of the equilibrium, with consideration of the expected payoff causing the equilibrium set to change dependent on the ratio of organizations to donors present within a particular site. In the future a more explicit consideration of competition effects within the organization objective function may be beneficial in advancing the model.

As it regards what the separating and pooling equilibrium explicitly say about the potential behavior observations, we can say that a separating equilibrium will always exist, and may help to explain why incidents in which areas receive more supplies and attention than are necessary, resulting in waste, occur. Beyond that, we are also able to characterize pooling equilibria and instances in which pooling can or cannot exist. Scenarios in which the pooling equilibrium exist and dominates the payoff from separating for both high productivity and low productivity organizations are outlined, and are shown to be dependent on donor beliefs about organization quality in a particular area. The Pareto dominant pooling structure shows that if the donor pool is large enough, and beliefs high enough, then organizations of lesser quality will find it beneficial to act as high quality organizations, through relief provision in a given area, while high quality organizations will not be incentivized to distinguish themselves. This result is substantiated by anecdotal observations of relief cases in which many newly formed and lesser known organizations crowd into high publicity relief theaters, but would require further empirical verification.

As a final caveat on the implications of the model, one should caution against over reading the results of the model, particularly with respect to the observed level of coordination within high publicity relief sites. While the signaling results can be considered to explain some of the resistance to coordination, they should not be read as accounting for the entirety of the reason for why coordination often times falls short of desired levels. While the model can perhaps explain much of the competitive dynamic, it does not rule out other possible explanations for coordination related issues. In particular it does not rule out that in general coordination is difficult in a highly de-centralized system and that resistance to coordination may be a result, in part, of the difficulties inherent in carrying it out within such a high stakes environment.

In the current model, the assumption is made that signaling via relief is the only way in which organizations can alter their expected contributions. In practice, however, organizations will often engage in direct fundraising campaigns to attract donor funds. An extension of the model in which direct fundraising is considered, along with signaling effects would be useful in making further characterizations about behavior in the face of informational asymmetries. Additionally, the decision about which areas organizations participated in was exogenously made. An extension whereby organizations can make this decision endogenously across a set of relief theaters would also be beneficial.

From an empirical perspective this paper highlights several areas which could benefit from empirical analysis. In particular, the existence of a Pareto dominant pooling equilibrium is dependent upon λ, which is the donor belief about the proportion of high quality organizations participating in an area. Behavioral studies of how donors form perceptions about the quality of organizations participating in various relief theaters would further ground the results of the presented model. Beyond the donor analysis, an assumption about signaling was made, in that it was assumed that higher levels of relief provision brought higher levels of exposure, and beyond a point increased expectation of donor funds. This exposure assumption is something that is testable via comparisons of organizational exposure around particular humanitarian events to levels of subsequent funding received by the organization of note. Lastly, the parameters $\bar{\theta}$ and $\underline{\theta}$ were used to represent high productivity and low productivity organizations, respectively. However, in practice, we know that there are differences in the quality of organizations, but an appropriate estimate of the values of these parameters is not readily accessible. Work to derive appropriate characterizations of productivity in the humanitarian environment is necessary going forward.

The presented model can be considered a first step toward the quantification of the market for humanitarian relief, which itself can be considered a subset of the philanthropic marketplace. There have been several papers which have grappled with how the market for philanthropy can be defined, with most falling into the category of conceptual frameworks. While a specific niche of this marketplace was considered, it is the author's belief that this model can be extended to include a more holistic analysis of charitable giving. Future work into model refinement and development from a quantitative perspective is crucial in advancing best practices as it concerns actual relief provision, and the maximization of its effectiveness. As motives and behavior are better understood, through both qualitative and quantitative research, the better institutions and policy can be designed with the aim of aligning incentives such that enhanced service for those in need is the ultimate outcome.

Chapter 3 considers similar issues as it relates to the influence of information on donor and organization behavior. It builds off the assumptions and results presented in this chapter, but is complementary in that it takes the perspective of search, in considering how donor's and organization's interact around information and giving.

2.6 Appendix: Equilibrium Refinement [17]

The previous section establishes a range over which various types of equilibrium can exist. However, even within this range, there are an infinite number of feasible equilibrium, and so the question of which equilibrium to focus on persists. Several *reasonable-belief* refinements have been proposed to help provide focus on a smaller subset of the abundant perfect Bayesian equilibrium (PBE) usually resulting from signaling games. Below, we apply several of these refinements in a progressive manner. Each of these refinements is introduced with the thought that one can establish a set of PBEs for which beliefs at the equilibrium are reasonable with respect to the agreed upon construct.

Strict Dominance

Strict dominance, as a refinement, asserts the following proposition with respect to the presented signaling game.

A relief level $r \in R$ is a strictly dominated choice for type θ if there is a relief level $r' \in R$ such that

$$\min_{y' \in Y} \mathrm{E}_{MN}[\pi(r', y(r'), \theta)] > \max_{y \in Y} \mathrm{E}_{MN}[\pi(r, y(r), \theta)] \tag{57}$$

For each action $r \in R$ define the set $\Theta(r) = \{\theta : \text{there is no } r' \in R \text{ satisfying (57)}\}$

A PBE has a reasonable belief if, $\forall r \in R$ with $\Theta(r) \neq \oslash$, then $\lambda(\theta|r) > 0$ only if $\theta \in \Theta(r)$, and a PBE is a sensible prediction only if it has reasonable beliefs.

In this instance, because there is no upperbound on $y \in Y = \Re_+$, we find that there is no strictly dominated r for either $\bar{\theta}$ or $\underline{\theta}$, thus $\Theta(r) = \{\bar{\theta}, \underline{\theta}\}$, $\forall r \in R$. As a consequence this refinement does not rule out any of the proposed PBEs.

Strict Dominance in Equilibrium Responses

Another refinement, which extends the rationale developed in the strict dominance

[17] ***Refinement discussion adapted from Mas-Colell [59]***

example, is that of strict dominance in equilibrium responses. This refinement is built out of the same fundamental idea of strict dominance, but limits the space of acceptable y values to those which can be found in equilibrium responses. In this sense, the range of equilibrium responses y, over the set of relief levels, r, creates some reasonable bounds over the set of donations $Y = \Re_+$. More formally, for any nonempty set $\hat{\Theta} \subset \Theta$, let $Y^*(\hat{\Theta}, r) \subset Y_1 \times \ldots \times Y_N$ denote the set of possible equilibrium responses that can arise after relief level r is observed for some beliefs satisfying the property that $\lambda(\theta|r) > 0$ only if $\theta \in \hat{\Theta}$. In the sense of strict dominance in equilibrium responses we can now say that relief level $r \in R$ is strictly dominated for type θ if there exists a level r' with

$$\min_{y' \in Y^*(\Theta, r')} \mathrm{E}_{MN}[\pi(r', y', \theta)] > \max_{y \in Y^*(\Theta, r)} \mathrm{E}_{MN}[\pi(r, y, \theta)] \tag{58}$$

Using this notion of dominance we can define the set,

$$\Theta^*(r) = \{\theta : \text{there is no } r' \in R \text{ satisfying (58)}\}$$

In this sense a PBE has reasonable beliefs if for all $r \in R$ with $\Theta^*(r) \neq \oslash$, then $\lambda(\theta|r) > 0$ only if $\theta \in \Theta^*(r)$.

Application of this refinement has the ability to reduce the set of PBEs by a reduction of the Y-space to $Y^*(\Theta, r') = [\underline{y}^*, \bar{y}^*]$ for all relief levels r. This reduction occurs because, for any belief $\lambda \in [0, 1]$, the resulting Nash Equilibrium wage must lie between $\underline{y}^*$ and $\bar{y}^*$.

By restricting the space to those responses found in equilibrium, it follows that for a $\underline{\theta}$-type, any $r > \tilde{r} = r_{LBsepMN} = \frac{\underline{\theta} + 2\sqrt{(\frac{N}{M})(\bar{y}^* - \underline{y}^*)\underline{\theta}\mu}}{2\mu}$ is dominated by $\underline{r}^*$. Consequently it is not reasonable to hold the belief that $\lambda(\underline{\theta}|r) > 0 \; \forall \; r > \tilde{r}$. This condition requires that for $r > \tilde{r}$ that beliefs about the high types must be $\lambda(\bar{\theta}|r) = 1$. This restriction on beliefs requires, provided that $\bar{r}^* > \tilde{r}$, that a type $\bar{\theta}$ signal $\bar{r}^*$. However, if $\bar{r}^* < \tilde{r}$, and a separating equilibrium is desired it must be the case that $\bar{\theta}$ will maximize its payoff by signaling at $r = \tilde{r} + \epsilon$ slightly above $\tilde{r}$, where $\epsilon > 0$.

Additionally, strict dominance in equilibrium responses helps to rule out certain pooling equilibrium, and in some cases all pooling equilibrium. The refinement requires that for $r > \tilde{r}$, $\lambda(\bar{\theta}|r) = 1$, and as a consequence, we can rule out any pooling equilibrium such that the expected payoff from pooling, $\mathrm{E}_{MN}[\pi(\hat{y}^*, r^p, \bar{\theta})]$ is less than $\mathrm{E}_{MN}[\pi(\bar{y}^*, \tilde{r}+\epsilon, \bar{\theta})]$ the payoff from a deviation to the smallest separating level. In fact, if one considers the set of all potential pooling equilibrium levels $[r_{LBpMN}, r_{UBpMN}]$, then all pooling equilibrium can be ruled out if for all $r_p \in [r_{LBpMN}, r_{UBpMN}]$, $\mathrm{E}_{MN}[\pi(\hat{y}^*, r^p, \bar{\theta})] \leq \mathrm{E}_{MN}[\pi(\bar{y}^*, \tilde{r}+\epsilon, \bar{\theta})]$. In this scenario, a $\bar{\theta}$ organization will always find it beneficial to deviate from the pooling level to its most profitable separating level.

Equilibrium Dominance

Equilibrium dominance further strengthens the refinement proposed via strict dominance in equilibrium responses.[18] This refinement begins with an equilibrium payoff $\mathrm{E}_{MN}[\pi^*(\theta)]$ for type θ and asks the question, what relief levels, r, does this payoff dominate for a type θ? More formally, relief level r is *equilibrium dominated* for type θ in PBE $(r^*(\theta), y^*(r), \lambda)$ if

$$\mathrm{E}_{MN}[\pi^*(\theta)] > \max_{y \in Y^*(\Theta, r)} \mathrm{E}_{MN}[\pi(r, y, \theta)] \tag{59}$$

Subsequently, define for each $r \in R$ the set,

$$\Theta^{**}(r) = \{\theta : \text{condition (59) does not hold}\}.$$

[18]Equilibrium dominance finds its base in the distinction between the notions of "no chance at all", and the notion of "some chance," no matter how small that chance may be. In other words, there are some situations in which, even if it were to be presumed that the organization is a high type with probability one, the payoff that accompanies the necessary signal would still not be enough to improve the organization's current PBE payoff. However, there may be some organizations for which the payoff could be better than the PBE payoff if the donor assumes with certainty that the organization is a high type. As a consequence types for which there is no chance are ruled out, and the probabilities of the remaining types are updated accordingly.

In this instance a PBE has reasonable beliefs if for all actions r with $\Theta^{**}(r) \neq \oslash$, $\lambda(\theta|r) > 0$ only if $\theta \in \Theta^{**}(r)$.

This refinement condition not only rules out all the equilibrium that are ruled out under dominance in equilibrium responses, but also rules out all pooling equilibrium.[19] Given satisfaction of the single crossing property, and adherence to equilibrium domination, pooling equilibrium can be ruled out via the following argument:

The pooling level r^p has to be less than $\tilde{r}$, the lower bound on separating equilibrium. By the definition of single-crossing property the $\bar{\theta}$-type objective curve crosses under the $\underline{\theta}$-type curve. As such, any deviation by a $\underline{\theta}$-type to a relief level $r > r'$ decreases the $profit$ of the low productivity type, even if the new signaling level caused the donor to believe with certainty that the organization was of a high type.[20] Consequently, a deviation to $r \in [r', r'']$ must imply that the organization is of a high type with certainty. This breaks the stability of any pooling PBE, as the high type organization will always have incentive to deviate to some $r \in [r', r'']$. Thus, only the best separating equilibrium remains as a PBE of the game.

[19]This is with the caveat that all pooling equilibrium are ruled out, only when a high type does not prefer one to separation. As was presented in the paper, there are instances in which a high type organization may find a pooling equilibrium to be optimal.

[20]r' and r'' are defined as the relief levels that make $\underline{\theta}$ and $\bar{\theta}$ types indifferent between the pooling payoff and the high productivity payoff, respectively.

CHAPTER III

A TWO-STAGE DONOR SEARCH MODEL OF THE MARKET FOR HUMANITARIAN CAUSES

3.1 Introduction

The previous chapter builds a model of donor and relief organization interaction on the assumption that donors have difficulties in distinguishing between the quality of relief organizations, and consequently look for signals to help them come to a determination about the quality of a given organization. In turn, this chapter builds on the concept of the relationship between the donor and organization by considering the dynamic from a slightly different perspective. Underlying the dynamics of the relationship is still the notion that organization behavior reveals information to the donor about its quality. However, in this chapter, the dynamic is developed through a two-stage donor search model, in which the information sought by the donor is less about whether or not the organization is a high or low productivity organization, but more about the quality of the *match* between an organization and a donor. In this sense a match is considered to be a donor's intrinsic value for the work of a particular organization, and the extent to which a donor can find and internalize the benefits of such an organization is the basis of the presented model. Taking a step back from the context of humanitarian relief defined in the previous chapter, this chapter abstracts the discussion to a more generally defined charitable marketplace, and considers an environment in which their are multiple sectors (e.g. health, education, human rights, etc.), each being comprised of various organizations. In this way, the donor's decision about which organization to donate toward, is no longer exogenously made.

At its most basic level an organization is the sum of the individuals and activities of which it is comprised. In this respect there may often be a contrast between what an organization thinks it is, and what it actually is. In this vein, activities and individuals effect various output metrics of the organization. Two metrics of particular concern to this work are the exposure level (i.e. an organization's likelihood of discovery by a donor) and the transparency level of an organization.[1] Throughout, these metrics will, in tandem, be used as proxy representations of particular organization *types*. These two organizational levers are isolated to formulate testing scenarios,which allow for analysis, through simulation, of donor behavior in response to changes in the system relative to some baseline, via the derived model. As such, this approach provides a handle on potential behavioral implications of these variables, with subsequent policy insights. Furthermore, it is assumed that, in an almost cyclical way, a donor's behavioral responses to these metrics are significant determinants in guiding the decision making of charitable organizations. The extent to which this may or may not be true is a driving consideration of model development and is discussed within the chapter. The model and its subsequent analysis will also provide the basis for empirical analysis of the theory, in particular; match sustainment, longitudinal studies of organizational activities, congestion analysis, and the provision for a taxonomy of charitable causes.

The presented model is a modification of the Jovanovic's [49] model of job search in the labor market, and was chosen because of its ability to capture aspects of a sustained relationship between donors and charities. This is in contrast to product search models in which the consumer searches for the lowest price of a given product,

[1] The terms *transparency level* and *monitoring cost* will be used interchangeably throughout the chapter. When one speaks of an organization having a high level of transparency, it is akin to saying that the organization has a low monitoring cost. In both senses, it is easier for an individual to acquire information about such an organization when compared to an organization of a low transparency level and high monitoring cost.

given some search costs. Most models of job search presuppose a continuing relationship past the initial match point (given all parties involved are so inclined), and thus continuous benefits are realized in each period after the initial match. Additionally, and perhaps an even more important distinction is that the nature of this good requires a certain level of discovery and exploration to determine the true utility to a donor.

This donor search model attempts to help fill a gap in the body of research surrounding donor and organization behavior. In particular, there has been much work from a theoretical perspective on understanding *why* people give. Notions of prestige in giving, impact giving, intrinsic altruism, impure altruism, etc., are all closely aligned with this branch of donor research. However, in addition to this branch, there has also been research into understanding how organizations can best tap into the sometimes latent desires of individuals to give. From this standpoint, research into how different fundraising appeals effect giving came about (e.g. leadership giving, matching, direct mail appeals[41], etc.). In this respect the model seeks to better define the area in the middle of these two research areas via a specific modeling of the process through which the two entities are engaged. Furthermore, in addition to the descriptive antecedents, the model also lays the groundwork for the development of charitable markets in which stable matches between donors and organizations can be more readily developed.

Section 3.2 provides more background on the considered problem, and places the research within the framework of previous literature as regards donor search behavior, organization behavior, and the use of search models in general. Section 3.3 builds the case for the presented model, and subsequently defines its construction. Section 3.4 outlines a simulation of donor search behavior within a charitable marketplace, and provides analysis on observed results. Section 3.5 attempts to place the results in a wider context as it regards how organizations weigh tradeoffs in the allocation of resources, and implications of the model for the charitable marketplace as a whole. Section 3.6 highlights some of the significant results of the model, and outlines directions for future work and extensions.

3.2 Background and Literature

While the previous chapter introduced a subset of the literature on the economics of charitable giving and signaling, in this chapter we turn our attention to the literature on search, non-profit motives, and notions of what non-profit or philanthropic marketplaces look like in practice. In arriving at an understanding of what is meant by the market for charitable causes one must not only have a baseline understanding of the role of charities and non-profits within the public space, but also understand to some extent what their objectives are, and how their activities evolve. While this was touched on in the preceding chapter, particularly within the context of humanitarian relief organizations we consider these questions again within a larger framework.

Hansmann [42], in “The Role of Nonprofit Enterprise” attempts to develop a perspective on the role that private nonprofits play in the economy, distinct from that of government enterprises and for-profit organizations. In particular he develops the notion of the “non-distribution” constraint, which is the distinguishing characteristic between non-profit and for-profit entities.[2] In similarly considering the characteristics and motivations of non-profits, James [48] posits a model of nonprofit growth. In particular she considers the notion of cross-subsidization within nonprofits, and finds that organizations will often times have to undertake activities from which they derive little to no satisfaction, such that they can afford to provide “high-value” services. In particular, this notion will become important when considered within the context of results from the donor search model. Weisbrod [102] and Holtman [46] offer further

[2] “non-distribution” implies that any profits accrued by the organization may not redistributed to individuals who exercise control over their organization, but instead must be reinvested within the organization to further the production of services and goods.

explanations for the existence and role of nonprofits, with an emphasis on their ability to efficiently provide public good, for which the for-profit or government sectors are not able to suitably provide.

The extent to which one is able to model a market for charitable goods in part rests on the assumption that competition exists within such a market. It was shown anecdotally in the previous chapter that competition among non-profits exists within the market for humanitarian relief. To this extent, quite a bit of work has been done in characterizing competition among a larger set of nonprofit entities. Bilodeau and Slivinski [17] consider why rival charities exist, with the primary motivation being that individuals can exert control of the mixture of public goods provided by operating such organizations. In particular, Rose-Ackerman [79], Feigenbaum [33], Tuckman [98], and Pepall et al. [71], all consider how competition within the nonprofit sector effects organization behavior as it regards resource allocation and efficiency. Rose-Ackerman shows how competition for donations can force organizations to spend an "excessive" amount of resources on fundraising. Feigenbaum develops a model of competition in the nonprofit sector using US medical research charities as a case study. She uses a four-firm concentration ratio as a measure of intramarket competition, and finds that increases in concentration lead to a negative impact on the amount of funds allocated to research. Along these same lines Castaneda et al. [22] use measures of market concentration to consider the effects of competition across a larger set of nonprofit sectors, and find similar results to Feigenbaum. Pepall et al. examine competition in the context of the religious marketplace and find that churches compete via expenses on charitable services.

Along the lines of the notion of transparency in the presented model, Frumkin and Kim [34] consider whether increased organization efficiency is rewarded via increased donor contributions within the charitable marketplace. In particular they consider whether it is economically beneficial to position one's organization as being administratively efficient relative to other organizations. Using panel data, and expense ratios as measures of efficiency they find that there are no significant gains in contributions for those organizations which are more efficient.

In the context of this chapter understanding why nonprofits exist, and how their behavior is influenced by competitive pressures is useful in contextualizing the results of the simulated search model, and in developing a functioning market of humanitarian causes. However, to develop a model of the marketplace, how the donor interacts with the aforementioned organizations most be modeled appropriately. Expanding on the factors introduced at the outset, namely exposure and transparency, Sargeant [84] develops a conceptual model of donor behavior. This model, along with other factors are considered within the context of economic search theory.

Much of the development of the donor search model builds on the results that lay at the foundation of research on economic search theory. Search theory, at its core, recognizes, the individuals make decisions based on the information they have at given point in time, and that in general better decisions are made when more information is available. As such, how much information an individual gathers during the course of the decision making process depends, in large part, on the costs associated with information gathering. These costs, in an economic sense are considered to be search, or transaction costs, as outlined by Williamson [104], and can be inhibitors to effective search, in the sense that one may be forced to make a less than optimal decision because it becomes too costly to obtain more information. Stigler's [95] seminal essay on the economics of information acknowledges as much, and considers the role of information within economics. Rothschild [83] offers a survey of the literature that can be considered derivatives of Sitgler's initial outline. While the concepts around search models can be applied in a multitude of settings, each model retains the same basic structure at its core.

Many of the foundational results in search theory have been derived from models placed in the setting of job search as defined by Stigler's [95] initial work on information in the labor market, and extended by McCall [60] in classifying optimal stopping conditions for laborers seeking employment. Yashiv [108] offers a recent survey of literature with respect to search within the labor market and its role in facilitating macroeconomic analysis. Becker [12], however, defines a theory of marriage via search and considers how matches within a frictionless "marriage market" occur, finding that individuals tend to match in a positively assortive manner along physical characteristics, and negatively in wage rates and other household substitutes. Atakan [9], and Shimer and Smith [88] extend Becker's work by considering how output changes when cost is associated with search in this market.

Jovanovic's model of job search provides the basis upon which the presented donor search model rests. Similarly, Wilde's [103] model can be considered in the same vein, with both offering a level of discovery as it concerns the quality of the information received before agreeing to accept a job. As such, both models consist of multiple stages with a new decision at each stage, and can be used to explain why job quits may or may not occur within the labor market. The remainder of the section considers why the canonical model of job search is not sufficient to model the donor market, with a discussion of how Jovanovic's model is applied occurring in Section 3.3.2.

The research on economic search is vast, with many variations and applications of the the economic search problem. These variations, of which the presented model is also one, all emanate in some respect from a basic model of search. As discussed in Lippman and McCall [53] the foundational economic search model provided in the context of the labor market is one in which there is some worker seeking a job that will provide him with an acceptable wage. The worker, at each stage, must pay a cost c to find out how much he will be offered for a particular job.[3] Conditional on a

[3] c can be equivalently thought of as the opportunity cost of search in a given period.

job offer the worker then either accepts the offer permanently, or rejects the offer and repeats the same process next period for a new wage offer. This process continues indefinitely, with no discounting for future wages, and without recall.[4] Underlying this simple model are several assumptions that shape the nature of the solution to the problem of when a worker should accept an offer.

It is initially assumed that the worker is risk neutral, so that he is indifferent between a current wage offer and an equivalent expectation of future wage offers. Furthermore, there is a known distribution of wages, such that the worker is able to formulate a mathematical expectation of future wages. The cumulative distribution of wages, $F(\cdot)$, provides the source of uncertainty in the model for which search becomes necessary. Given this setup, and the underlying assumptions, the solution takes the form of a cutoff value, where for wages offered above the cutoff value the worker accepts, and for wages below the cutoff value the worker rejects and continues searching.

The foundational model is presented to both provide a basis for the extended model presented in this paper, but also as an expository tool to understand why the model must be extended in order to capture some of the desired attributes of the market for humanitarian causes. In particular, given the issues under consideration in this chapter, an appropriate model must capture the following:

- Unique valuations across different causes and organizations from a donor perspective.
- Organizational discovery [5].
- A range of transparency levels across organizations, and monitoring costs associated with them.

[4] "With Recall" would allow the worker to continue searching and recall any previous offer that he has seen during his search process, and accept it, at anytime he wishes. In this simple model there is no difference between search with recall and without recall.

[5] This is akin to gradual learning about an organization's quality.

- Alternative uses for money (i.e. If a donor does not find a suitable donation opportunity then they can place their money elsewhere for the time being).

All of the items, with the exception of organizational discovery, can be packaged in a one-stage framework, and could conceivably be handled by the foundational model. However, discovery requires, at minimum, a two-stage framework and cannot be handled by the foundational model. The desire for discovery in the model is drawn from the use of Andreoni's impure altruism model [3] as the basis for donor utility construction. This point, along with the remainder of the presented model is explained more throughly in the following section.

3.3 A Two-Stage Donor Search Model

3.3.1 Assumptions

To facilitate model development, a few basic assumptions about the dynamic under construction are outlined:

- There are altruistic donors who want to give money to charitable *causes*.
- Individual donors have preferences over which of these causes are most important to them.
- Within these causes, the donor has preferences over which organizations he would like to contribute toward.
- The donor *knows* his preferences, but must take time to find the organization which best matches them (i.e. information about best matches is not readily available, and may require a commitment of the donor's resources to obtain it.)
- The humanitarian organizations have preferences over certain causes as dictated by mission. However, they would still like to provide assistance to as many areas a possible, but are constrained by resources.

- Humanitarian organizations have preferences over the areas they participate in.
- Humanitarian organizations need, and want donor funds.
- Humanitarian organizations will act strategically to obtain donor funds.

3.3.2 Model Development

The Jovanovic model, a two-sided search model of the job market, can be modified to allow for a one-sided agent-based model of donor interaction with the humanitarian marketplace. Specifically, the proposed model acts as a descriptive model of donor search. Below, the initial set of parameters, and the progression of the model are defined, along with a discussion of several assumptions and conditions used within the model. Philip Nelson, in his seminal work ([69]), proposed a dichotomous classification of goods as either *search goods*, or *experience goods*. Search goods are goods which have characteristics that can easily be evaluated before they are purchased. In contrast, experience goods must be purchased in order to discern quality. In this paper the provision of humanitarian aid is considered a public good that the donor wishes to contribute toward via donation to a humanitarian organization. It is not clear whether the purchase of aid for others through a humanitarian organization is a search or experience good from the donor's vantage point, in that the donor may never be entirely sure about the quality of the good he has purchased. However, for the purposes of this paper and the presented model, it is assumed that the characteristics of this public good fall closer to that of an experience good.[6]

The donor search process is modeled around the following story, adapted from Jovanovic's model of job search. The hypothesis that both sides of the job match (i.e. workers and employers) behave optimally and only gradually learn about the quality of the match between the two, on which Jovanovic built his model, is transferred to

[6]As mentioned in the preceding chapter, Darby and Karni [30] discuss the notion of a credence good, or a good for which the true value is never known to the purchaser. The purchase of aid, via donations to humanitarian based organizations could be considered to be such a good.

the presented model. In this model a *risk neutral* donor *samples* an organization to ascertain the quality of its work, and his experience as a donor to that organization. This initial sample phase dictates to the donor the nature of his relationship with the organization going forward. In this initial model the organization's action set is restricted to $\{Accept, Reject\}$. The organization either accepts donated funds, or rejects the funds. Working under the assumption that the funds are "no strings attached," the optimal behavior for an organization is to always accept, which allows the market to be modeled as a one-sided matching.[7] In this scenario, as alluded to in the previously defined assumptions, there exists a set of donors, all of whom are interested in giving this period provided that giving exceeds the opportunity cost of not giving. Furthermore, they have preferences over the type of work the organization does, and coupled with their perceived productivity of the organization, they experience varying benefit depending on the organization they ultimately end up donating to. As a consequence, given a heterogeneous donor pool, the match (or *fit*), that each donor experiences with a given organization will vary.[8] With this in mind, a process in which a donor, via some mechanism, encounters a potential recipient organization is considered.

The donor, having some exogenous level of information available to him about a given organization formulates an initial belief about the benefit he would receive from making a donation to this organization. This initial view of the benefit from the organization match will be called s_{ij}, and can be viewed as the *warm-glow* experienced by a donor i upon an initial donation to organization j, similar to what Andreoni describes. Accordingly, the donor makes a decision about whether or not to donate to

[7] "No strings attached" is defined such that the organization is not restricted in how it uses any donations it may receive. If "with strings attached" is allowed, it may be the case that the organization will reject the funds because the requirements associated with a donation may not be in line with its core activities or goals.[10]

[8] See Roth and Sotomayor [82] for a more in-depth discussion of game-theoretic matching in markets.

this organization in the current period, or to hold off and search for a better match for his humanitarian interests. Also under consideration is that a donor must pay some cost, c_j, to invest in the organization and to subsequently monitor the behavior of the organization. Monitoring is necessary, in that the donor needs to acquire information, *ex post*, in order to come to a better understanding of how well he matches with the organization and its outcomes. In this sense, the donor's benefit from donating in this initial period is the experience of the *warm-glow*, as defined by s_{ij}, less the cost of monitoring (i.e $s_{ij} - c_j$). If the donor chooses not to commit to the current organization he goes back to the initial phase and encounters another organization via the same introduction mechanism. However, if the donor chooses to pay c_j and donate, in the next period they are shown the true value of the match, x_{ij}, and then presented with the option of either continuing with this match and leaving the search process or discarding their current match and continuing the search process.[9]

3.3.2.1 Definitions

Several parameters, which will be used going forward, are defined.

Time:

$T \equiv$ The set of time periods, indexed, $t = 1 \ldots |T|$.

Agents:

$N \equiv$ The set of donors, indexed, $i = 1 \ldots |N|$.

$M \equiv$ The set of relief organizations, indexed, $j = 0 \ldots |M|$, where $j = 0$ is an index included to represent the donor (i.e. A donation to organization $j = 0$ is equivalent to a donor deciding to keep his money).

[9] It may be a bit presumptuous to assume that the donor can ascertain the true value of the match after one period, but this construction is nonetheless presented as a baseline example. Extensions, whereby the donor gradually learns of the true value can also be considered.

Donor Parameters:

$x_{ij} \equiv$ The *benefit*, or value of the match, to donor i from making a contribution to organization j.[10] Values of x are i.i.d with distribution $N(\mu_x, \sigma_x^2)$.

$\epsilon \equiv$ Random noise within the system that obscures the true value of x_{ij}. ϵ is i.i.d. with distribution $N(\mu_\epsilon, \sigma_\epsilon^2)$.

$s_{ij} \equiv$ The initial warm-glow perception to donor i of a donation to organization j. More explicitly, $s_{ij} = x_{ij} + \epsilon$, which makes s_{ij} i.i.d. with distribution $N(\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)$

$p_{ij}^t \equiv$ The probability that donor i encounters organization j in period t. When p_{ij} is used the probabilities are stationary. $\sum_{j=1}^{|M|} p_{ij} = 1$ for all i.

$\beta \in (0,1) \equiv$ Donor sensitivity to delay, or discount value on future rewards. Values close to 0 signify an impatient market, in which donors severely discount rewards accrued pass the current period. Values close to 1 is indicative of a market in which donors make little distinction between current period rewards and future rewards.

Organization Parameters:

$c_{ij} \equiv$ The cost to donor i of monitoring organization j. The distribution of c within a particular marketplace is context dependent, but can be considered to be bounded on the interval $[\underline{c}, \bar{c}]$.

3.3.2.2 Progression

The progression of the model is outlined below.

Step 0 (*Initialization*):

[10] At this point, no suggestions as to what the actual dollar amount of the donation is, are made. The assumption is made that the donor wants to donate some money, and that they donate such that, under perfect information x_{ij} would be realized.

0a. Define Values for M, N, and T.

0b. Define the $|N| \times |M|$ Introduction matrix, $\mathbf{P}$, where $p_{ij} \in \mathbf{P}$.

0c. Define parameters for $N(\mu_x, \sigma_x)$ and $N(\mu_\epsilon, \sigma_\epsilon)$.

0d. Define the Cost vector $\mathbf{c} \in \Re^{|M|}$, where $c_j \in \mathbf{c}$ denotes the cost of exploring organization j for all donors i. [11]

Step 1 (*Pairing and Viewing*):

1a. If donor i does not have a 1st stage match, then he *randomly* encounters organization j with probability p_{ij}^t in the current period. Go to **step 1b**, otherwise **step 1c**.

1b. s_{ij} is generated according to $N(\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)$ and revealed to donor i. Go to **step 2**.

1c. If the donor i has a 1st stage match, then go to **step 4**.

Step 2 (*Decision Evaluation*):

2a. Donor i makes a decision, based on his action set and guided by his *decision rule*, whether or not to pay c_j this period and *match* with j.[12] Go to **step 2b**.

2b. If the donor decides to pay c_j, then go to **step 3**, otherwise **step 2c**.

2c. If the donor declines to pay c_j, and $t < T$, then move to **step 1**. Otherwise terminate the match process.

Step 3 (*1st Stage Payoff*):

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[11] Of course, as noted above, the cost may be dependent on both the donor's type, and the relief organization's type, wherein the cost would be $c_{ij} \in \mathbf{C}$, where $\mathbf{C}$ is a $|N| \times |M|$ Cost matrix. However, we initially consider the case in which the cost is unique to the relief organization, and homogeneous across the set of donors, such that $c_{ij} = c_j, \forall i$.

[12] The particular timing of c_j is not important (i.e. whether payment occurs at the beginning, middle, or end of the 1st stage). What is important is that it is paid before stage 2 commences. In reality c_j will be an on going cost throughout the 1st stage, but is considered a one time payment for ease of analysis.

3a. The donor receives the 1st stage benefit, s_{ij}, and total payoff $s_{ij} - c_j$. Go to **step 1**.

Step 4 (*Information Reveal*):

4a. The donor receives $\tilde{s}_{ij}$, an *updated* view of the organization match s_{ij}, which is closer to the true value of x_{ij}. [13] Go to **step 5**.

Step 5 (*2nd Stage Decision*):

5a. Allowing that $\tilde{s}_{ij}$ allows for an update in beliefs about the true match, x_{ij}, donor i decides to either accept the benefit $\mathrm{E}[x_{ij}|\tilde{s}_{ij}]$ and match with j forever, or rebuff organization j, and seek a new match.[14].

5b. If the donor accepts, a match is solidified, and he leaves the system. If $t < T$ then go to **step 1**, otherwise terminate the match process.

5c. If the donor rejects j and $t < T$ then go to **step 1**, otherwise terminate the match process.

Figure (12) provides a schematic diagram of the above algorithm. Below, more technical elements of the model progression and decision process are discussed, with special attention paid to consideration of the exposure distribution and cost construction.

3.3.3 Discussion

Both the exposure level and the cost have been defined as proxies for a given organization, and in this sense it is important to understand how they can define an underlying organization, and how they function in this model. Specifically, it is important to understand how they may be manipulated, how they differ, and how each adds value to the presented model.

[13] For ease of computation, let $\tilde{s}_{ij} = x_{ij}$, initially.

[14] Again, if the true value is revealed in step 4, then $\mathrm{E}[x_{ij}|\tilde{s}_{ij}]$ can be replaced by x_{ij}

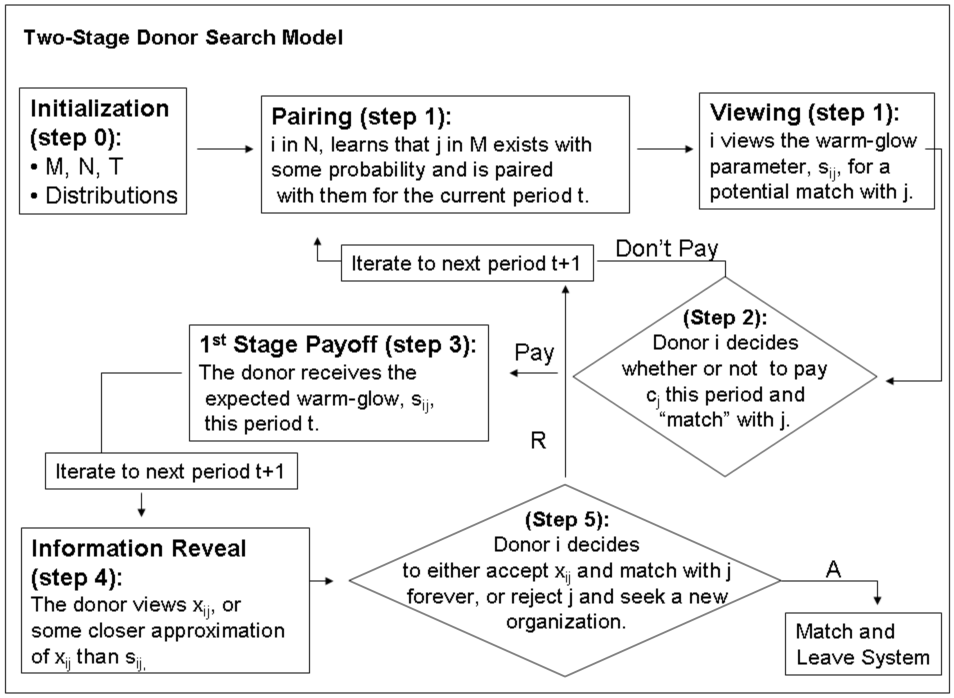


Figure 12: Donor Search Model

There are, in effect, two ways to use these levers in modeling. The levers can either *exogenously* or *endogenously* evolve with the model. Exogenous evolution is such that these levers are controlled outside of the model, and can be defined *a priori* to coincide with strict testing scenarios. In the instance that organizations are allowed to interact with and adjust the levers during the course of the model progression then they are considered to be endogenous to the model. The initial cost and distribution constructions, along with the interaction rules, can also be used to define testing scenarios, but in a different sense than the exogenous setting. Throughout we will assume an exogenous setting, with endogenous evolution of the cost and exposure variables left as an extension for future work.

3.3.3.1 *Cost Construction*

As outlined in the introduction, the primary goal of this model is to understand how the consideration of search costs, monitoring costs, and exposure in providing humanitarian aid can be used in explaining the behavior of relief organizations. Control and manipulation of the cost parameter, in addition to the exposure distribution, allows for the creation of scenarios from which to analyze the cost effect. The cost parameter, c_j, for a given organization can be viewed as being comprised of two components. The first component can be considered to consist of standard structural costs associated with making an investment in a charitable organization, and will be fairly standard across all organizations.[15] The second component of the cost is organization specific and can be considered the cost, to the donor, to stay informed about organization activities and mission completion. In this sense, the donor has to pay the cost in order to find out how well the organization matches with his interests, beyond the initial warm-glow experience.

Given the explanation of what the cost represents, it is also important to consider what the manipulation of the cost means (i.e. why might the cost for one organization be smaller than for another?). Making the assumption that all organizations start out with the same cost, an organization could reduce its cost through increased transparency or increased media attention. Increased transparency can be accomplished through organization provided updates to donors about mission success, effectively reducing the cost to donors of finding this information on their own. Increased media attention can be accomplished through strategic placement in high publicity areas and causes, or through organization promotional events showcasing their work. As will be discussed in Section 3.3.3.2, organizations are also rewarded in the model via

[15]This might be considered the cost of the actual transaction.

increased exposure probabilities for working in high attention areas, and so it is possible, via strategic placement, for an organization to both increase transparency and exposure. Consequently, the exposure effect is double counted to a point.[16] [17]

3.3.3.2 Exposure Distribution

In pursuing the primary goal of the modeling exercise, it must be that this model provides a test bed for the assumptions that have been put forth about the behavior of donors and relief organizations. Accordingly, the model should allow for the existence of several levers, which can be pulled to varying degrees, to test these assumptions. The aforementioned cost construction is one of these levers. However, in addition to this lever, the exposure lever is available. The exposure distribution is defined via the exposure (or introduction) matrix in the model. How the distribution is constructed is directly related to where an organization positions itself as it regards the various humanitarian causes that persist at any given time.[18] This matrix defines the probability that a given donor comes into contact with a particular organization during each period of the model. Taking the view that higher publicity areas yield higher probabilities of introduction, this distribution can be used, in addition to the cost variables, as a proxy for an organization's positioning on the *publicity spectrum*

[16]While this may seem to be a problem, in that to much weight may be given to the exposure effect, the situation mirrors reality to an extent. Furthermore, considering the duel role of the exposure factor allows for isolation of the effects that doing work in high publicity areas has on donor behavior. For instance, does working in these areas payoff because of ease of monitoring, increased exposure opportunities, or both? This question can be answered through carefully designed testing scenarios.

[17]As an aside, the cost representation here places this model in a unique space, in the sense that the benefit the donor experiences is to some extent controlled by his or her effort. If one considers Andreoni's model of impure altruism there are both private and public effects from giving to an organization, with the private effects being experienced through the act of giving itself. The public effects, and particularly for humanitarian causes, exist, but unless a donor is informed about the organization work after his gift, are not experienced by this donor. The model does not allow for the choice between paying c_j or not. However, a model in which the choice could be presented can be imagined. In such a model those who paid c_j would experience both public and private effects of their gift, and those who did not would experience only private, or warm-glow, effects.

[18]It is important to emphasis the distinction between the exposure probabilities, which guide the chances of a given donor encountering a specific organization, and the match distribution. The match distribution says that for each matched donor and organization pair, the quality of the match, x_{ij}, is normally distributed, whereas exposure defines the probability of that initial introduction occurring.

Table 1: Example Cause Universe

Cause	Publicity Level	Mission Alignment
1	High	2
2	Med	3
3	Low	1
4	Low	3

Table 2: Exposure Translation

Cause	α-Weight	Probability of Exposure
1	α_1	$\alpha_1 \frac{1}{M_1}$
2	α_2	$\alpha_2 \frac{1}{M_2}$
3	α_3	$\alpha_3 \frac{1}{M_3}$
4	α_4	$\alpha_4 \frac{1}{M_4}$

of relief causes.[19] Table 1 provides an example of how the space of humanitarian causes, and their associated publicity levels, can be translated into exposure probabilities. Assume a world with M organizations and 4 causes as defined in Table 1. Each cause has an associated publicity level (High, Medium, Low), and the number of organizations working on that cause can be defined as M_k, such that the number of organizations working on cause 1 is M_1. If the assumption is made that each organization within a specific cause has the same probability of exposure, but that exposure across causes is proportional to the publicity level, one can construct exposure probabilities as in table 2, where $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. By weighting the exposure probabilities across causes a characterization of the type of work a given organization is engaged in can be made.

While exposure for a given organization is tied to the publicity level that their chosen cause receives, a connection between the relevancy of the cause to the organization's mission and its exposure probabilities is not offered. For instance, the fact

[19] Informally defined, the *publicity spectrum* simply acknowledges that among the universe of humanitarian causes, some are more prominently considered within the public sphere than others. For instance, in recent years beast cancer charities have received prominent exposure will kidney disease charities have received much less in comparison.

that cause 3 has high mission relevance to this organization does not in any way make it more desirable from an exposure standpoint than causes 1 or 2.[20] The mission relevance ranking can be useful in scenario construction and analysis, and can act as a guide in choosing initial exposure levels for a given organization. As an example, if the assumption is made that an organization eschews publicity for mission relevance their initial exposure level, p_{ij}^0, can be defined in accordance with the cause that they value the most. Subsequently, if organizations are allowed to alter their behavior and placement of resources, such that at the end of a scenario run $p_{ij}^0 \neq p_{ij}^T$, then the distance defined by $||p_{ij}^0 - p_{ij}^T||$ can be used as a measure of how far an organization strayed from its core mission goals in the pursuit of funding. Even if the model is static, and exposure levels are exogenously defined, this particular scenario can still provide quite a bit of insight when compared with others.[21]

3.3.3.3 Accept or Reject

In this section the donor's decision process is considered more throughly. Of particular consideration is how the donor in the modified Jovanovic model makes a decision about whether to initially donate to a particular organization, and furthermore how the decision about whether or not to sustain the match is formulated. The "accept or reject" proposition of the donor is considered in a three stage format, starting from the last stage of the decision process.

Starting at stage 3, the worker now knows $x = x_{ij}$ for its current match. Let $J(x)$ be the expected present value of the benefit afforded a donor at stage 3 who has a known match x in hand, and who behaves optimally. Accordingly, the value of a match x is given by $x + \beta J(x)$, where β is considered to be a discount factor on

[20] A scale of mission relevance to represent how a particular cause relates to a specific organization's stated mission is used. A relevance level of 1 denotes high relevance, and a level of 2 denotes a slightly lower level of relevance, and so forth.

[21] Throughout this chapter exposure levels are exogenously defined. Endogenous exposure levels can be considered as an extension.

future benefits. A donor who rejects the match gets his reservation benefit, x_{i0}, in the current period, which is defined by $r = x_{i0}$ going forward. Additionally, a donor who rejects this match gets to draw a new match next period, with expected present value Q, so that the current period payoff of rejection is $r + \beta Q$. Thus, the Bellman equation for stage 3:

$$J(x) = \max\{x + \beta J(x), r + \beta Q\} \tag{60}$$

Given that x and $J(x)$ increase in x, and $r + \beta Q$ remains constant, one can define the functional form:

$$J(x) = \begin{cases} x + \beta J(x) = \frac{x}{1-\beta} & \text{for } x \geq \bar{x} \\ r + \beta Q & \text{for } x \leq \bar{x} \end{cases} \tag{61}$$

The policy guides the donor to reject the match if $x \leq \bar{x}$, and accept if $x \geq \bar{x}$, where $\frac{\bar{x}}{1-\beta} = r + \beta Q$.

Moving back a stage, to stage 2 of the decision process, the donor is confronted with a current warm-glow benefit $s = s_{ij}$, a cost of exploration $c = c_j$, and the mathematical expectation of x_{ij} in the next period, given s_{ij} in this period.

Let $m(s, c) = s - c$, where m's dependence on s and c may be suppressed by writing m. Let $V(m)$ be the expected present value of matching benefits at the second stage to a donor who has warm-glow of s and cost c currently in hand, and who behaves optimally. A donor who rejects the match receives $r + \beta Q$. In this sense one can write the Bellman equation as below, where the distribution of x is conditioned upon the observation s.[22]

[22]Baye's rule, and Kalman filtering can be used to derive the distribution of x given s. See the appendix for more discussion of filtering in this example.

$$V(m) = \max\{m + \beta \int J(x) dF(x|s), r + \beta Q\} \tag{62}$$

$$= \max\{s - c + \beta \int J(x) dF(x|s), r + \beta Q\} \tag{63}$$

Similar to $J(x)$ one can define a functional form which depends on an optimal reservation policy:

$$V(m) = \begin{cases} m + \beta \int J(x) dF(x|s) & \text{for } m \geq \bar{m} \\ r + \beta Q & \text{for } m \leq \bar{m} \end{cases} \tag{64}$$

The first stage can now be established, which is the pre-exposure expected present value of a match to a donor who did not have a match last period, and is about to encounter a potential match this period.

$$Q = \sum_{c=\underline{c}}^{\bar{c}} \int V(s-c) f(c) dG(s|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2) \tag{65}$$

Where $G(s|\cdot)$ is the normal distribution with altered parameters to reflect the distribution of s, and $f(c)$ is the p.d.f of the cost distribution.

Satisfaction of equations defined by $J(x)$, $V(m)$, and Q will yield the donor's optimal policy when seeking matches. Guided by Bellman [14], an iterated solution method is considered in the appendix.

Proposition 1: Given $J(x)$, $V(m)$, and the identity $\frac{\bar{x}}{1-\beta} = r + \beta Q$, it is always the case that $\bar{x} > \bar{m}$ (i.e. the true match cutoff $\bar{x}$, will exceed $\bar{m}$, the cutoff for the warm-glow cost combination).

Proof. Equation (66) defines an implicit equation for the reservation $\bar{m}$ via the functional representation of $V(m)$, such that,

$$V(\bar{m}) = \bar{m} + \beta \int J(x) dF(x|s) = r + \beta Q \tag{66}$$

Preceding forward, and carrying out the requisite substitutions:

$$\bar{m} + \beta \int_{-\infty}^{\bar{x}} J(x) dF(x|s) + \beta \int_{\bar{x}}^{\infty} J(x) dF(x|s) = r + \beta Q = \frac{\bar{x}}{1-\beta} \tag{67}$$

$$\bar{m} + \frac{\beta \bar{x}}{1-\beta} \int_{-\infty}^{\bar{x}} dF(x|s) + \frac{\beta}{1-\beta} \int_{\bar{x}}^{\infty} x dF(x|s) = \frac{\bar{x}}{1-\beta} \tag{68}$$

$$\begin{aligned} \bar{m} + \frac{\beta \bar{x}}{1-\beta} \int_{-\infty}^{\bar{x}} dF(x|s) + \frac{\beta \bar{x}}{1-\beta} \int_{\bar{x}}^{\infty} dF(x|s) \\ - \frac{\beta \bar{x}}{1-\beta} \int_{\bar{x}}^{\infty} dF(x|s) + \frac{\beta}{1-\beta} \int_{\bar{x}}^{\infty} x dF(x|s) = \frac{\bar{x}}{1-\beta} \end{aligned} \tag{69}$$

$$\frac{\beta \bar{x}}{1-\beta} + \frac{\beta}{1-\beta} \int_{\bar{x}}^{\infty} (x - \bar{x}) dF(x|s) \Rightarrow \bar{x} - \bar{m} > 0 \tag{70}$$

□

Given the defined value functions, it still remains to be shown that there exists a unique optimal policy for when to accept and reject in each situation (i.e. does there exist unique solutions for $\bar{x}$ and $\bar{m}$). These issues are addressed in the appendix.

3.4 Simulation and Results

This section seeks to answer questions about how the marketplace evolves given various structures, and how individual donors and organizations are effected. Primarily through the manipulation of the cost and exposure variables, along with variance in the number of organizations, do we consider some of the following scenarios,

1. For a given exposure distribution, what does the donor distribution look like if monitoring costs are uniform across organizations?

2. For a given exposure distribution, how does output change as monitoring costs are segmented into more categories?

3. How does segmented exposure impact organization and system outcomes?

The search model is implemented with Monte Carlo methods, with the aid of the Matlab programming language. In particular, the implementation process consists of two simulation phases that are discussed and analyzed below. The first stage of the process calculates the appropriate cutoff values for the two-stage accept or reject decision process found in the model. This section begins by considering the behavior of the cutoff values, and sensitivity of the results when parameters are adjusted. The second part of this section focuses on the full simulation of the donor search model proposed in Section 3.3. This second phase simulation takes as input, along with additional parameters, the cutoff values generated in the first phase of the process. In this section the preceding scenarios are constructed and analyzed alongside the presented output.

3.4.1 Behavior of the Cutoff Values

The behavior of the cutoff values, specifically $\bar{x}$ and $\bar{m} = s - c$, that result from a given scenario analysis are considered. Sensitivity results are established relative to a baseline scenario, as defined below. The focus is not on absolute values, but on trends relative to some baseline. All parameter vectors will be defined by the input vector

$$\psi = (r, \beta, \{\mu_x, \sigma_x\}, \{\mu_\epsilon, \sigma_\epsilon\}, \{cSet\}, \{cDist\}), \tag{71}$$

where r is the reservation payoff, β is the discount parameter, and $\{\mu_x, \sigma_x^2\}$ and $\{\mu_\epsilon, \sigma_\epsilon^2\}$ are the mean and variance of x and ϵ, respectively. *cSet* is the set of cost levels, and *cDist* defines the distribution over the set. The baseline parameter set is defined by the vector,

$$\psi_{\text{base}} = (0, 0.5, \{5, 10\}, \{0, 1\}, \{(0, 5)\}, \{(0.5, 0.5)\}). \tag{72}$$

This vector produces the cutoff pair $(\bar{x}, \bar{m}) = (1.9232, 1.6272)$. It is from this pair that initial sensitivity results associated with the β parameter are described.

To understand what these values mean, it helps to relate them back to the initially presented search story. $\bar{m}$ is the first stage cutoff value, and is best understood as the combination of warm-glow, s, and the cost of monitoring (or transparency), c. Consequently, any combination of $s - c$, for a particular donor-organization pair that exceeds $\bar{m}$ will induce the donor to make an initial (first stage) contribution to the organization. Figure (13) provides a graphical representation of $\bar{m}$ and its connection to s and c values. The example defines a cutoff value of $\bar{m} = 2$, and defines all of the combinations of s and c which exceed the cutoff level. Accepted combinations are those for which $s - c$ lies on or above the line defined by m_{cutoff} in the figure, such that the combination $s = 6$ less $c = 3$ lies in the acceptance region, but $s = 2$ less $c = 1$ does not. A similar region can be constructed for the baseline cutoff value of $\bar{m} = 1.6272$.

While $\bar{m}$ is defined via two dimensions, $\bar{x}$ is defined only on one, the true value of the donor-organization match. $\bar{x}$ is the second stage cutoff, and if the donor's true match exceeds this level, the donor will then enter into an perpetual giving relationship with the organization that generates the match utility. In the baseline example, if a donor i experiences a match, x, greater than 1.9232 then he will accept, otherwise he will continue searching.

3.4.1.1 β Analysis

The $\beta \in (0, 1)$ value is presented as a discount parameter and measures a donor's tolerance for delay in receiving his payoff. A value of β close to 1 signals a high tolerance level, in the sense that the donor values next period payoffs almost as much as current period payoffs. If $\beta = 1$ then there is no difference, from the donor standpoint, of receiving a payoff in the current period or in the next period. In the

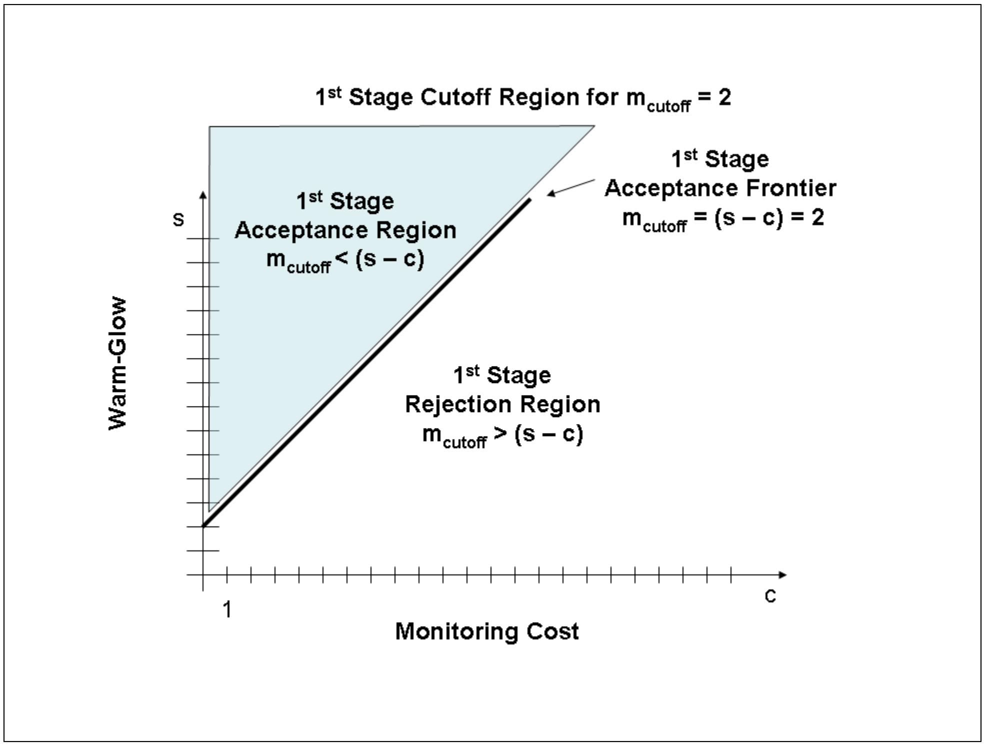


Figure 13: First Stage Cutoff Example

presented model, β could be more concretely viewed as the donor's willingness to wait on feedback from an organization, with higher values of β indicative of donors who are more patient. In figure (14) it can be seen that, holding all other parameters constant, increases in the β value leads to increases in both $\bar{x}$ and $\bar{m}$ values. This is not a surprising result, in that a donor with a higher tolerance for delay would also be willing to be more patient in his search, and consequently they can be more selective in their search process, which in this instance is akin to higher cutoff values.

3.4.1.2 Cost Analysis

Of particular importance to the proposed model is the effect of monitoring costs (transparency) on the search and acceptance behavior of donors. As previously discussed, the first stage cutoff value $\bar{m}$ is defined via the expression $s - c$, where c is the monitoring cost. In this analysis c is isolated in an attempt to distinguish its effects

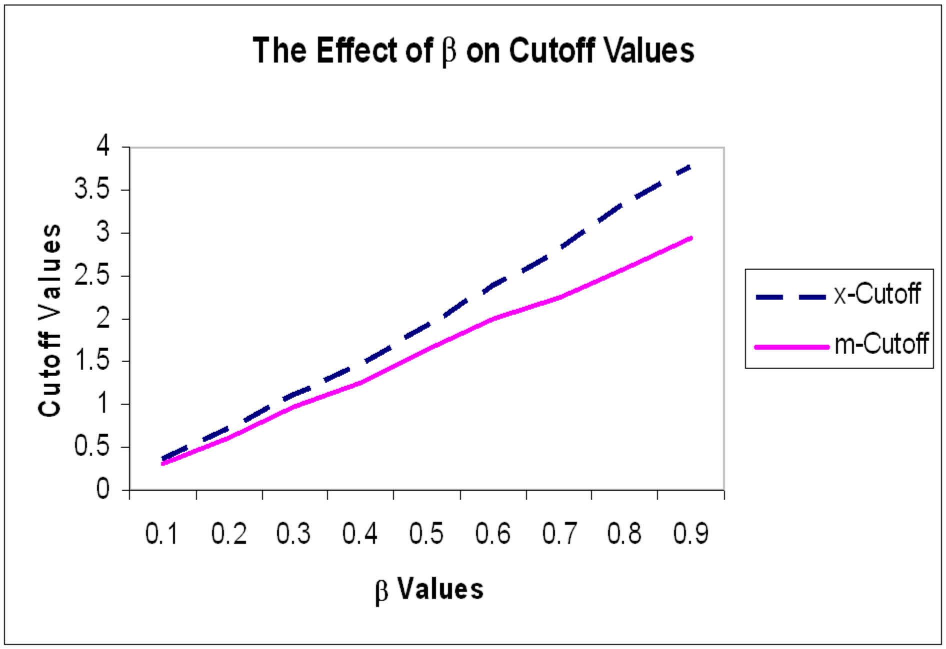


Figure 14: Effect of β on Cutoff Values

from the effect of the s distribution on the cutoff values. Furthermore, an attempt is made to distinguish between the effect of the magnitude of the c values and the dispersion of the c values. To distinguish between these effects two types of scenarios were run. In the first scenario, the baseline parameter set was altered such that there existed only one universal transparency level for all organizations. By making the cost equal across all organizations one is able to vary the magnitude of the universal c value to distinguish these effects from dispersion in some respect. Figure (15a) shows the effect of the cost across several scenarios, with the initial scenario being the baseline put forward above. The baseline scenario is then modified by increasing the reservation utility (r) from 0 to 5 in one instance, decreasing the expected match value (μ_x) from 5 to 0 in another instance, and by doing both in the scenario represented by Figure (15b). The following observations can be made across analysis of the various scenarios:

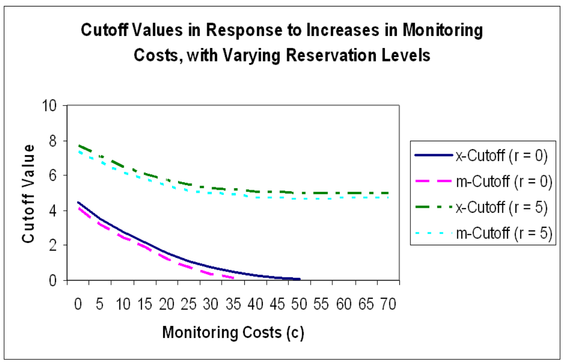
- In all presented cases an increase in the magnitude of monitoring costs is associated with a decrease in both the $\bar{x}$ and $\bar{m}$ values.

- Relative to the baseline case, an increase in r from 0 to 5 causes an across the board upward shift of the cutoff values, but maintains the decreasing trend associated with the baseline case. Additionally, an increase in the r value appears to have a tempering effect on the rate of decrease, as shown by Figure (15c). The decrease in the cutoff values occurs at a smaller rate for the higher level of r.

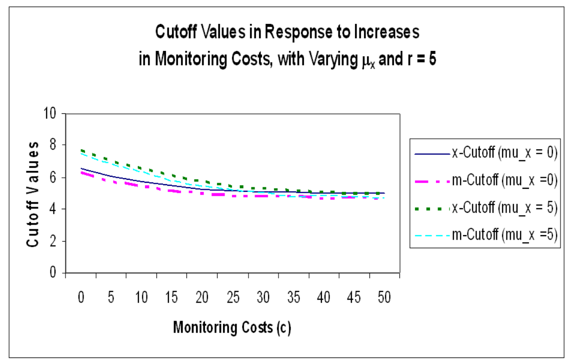
- Contrary to the effect of the change in the r value, shifts of the μ_x value do not appear to change the rate of decrease in a significant way. In fact, Figure (15d) seems to suggest that beyond a certain cost level the cutoff values may converge for the two cases.

- The third scenario, as outlined in Figure (15b), seems to indicate that the r value has a significant effect on the ability of changes in the μ_x value to translate to significant changes in the cutoff values. In particular, it is easily gleaned from Figure (15b) that the trace of the cutoff values from varying costs when $r = 5$, for $\mu_x = 5$ and $\mu_x = 0$ are very similar. Much more so than in the analog case of $r = 0$, as shown in Figure (15d). In isolation, a change in r from 0 to 5 appears to shift the cutoff values by at least a magnitude of 2. However, a change in the μ_x values by the same magnitude shifts the cutoff values by at most a magnitude of 2, with the difference decreasing as c increases. In total, this points to the notion that reservation values have a more significant effect on cutoff values than the mean values of x of similar magnitude.

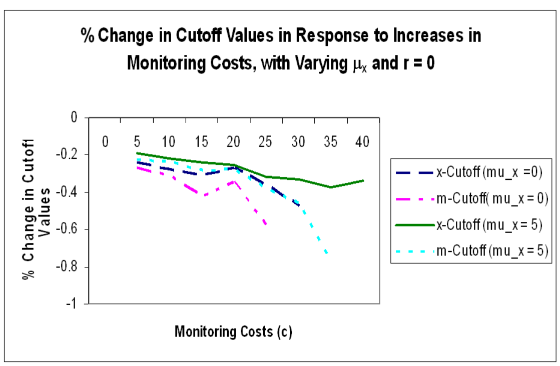
Resulting from this analysis, one of the primary questions to consider is why, from an intuitive standpoint, does an increase in cost cause a decrease in the cutoff values of both the first and second stage. If one assumes that the cost in this context



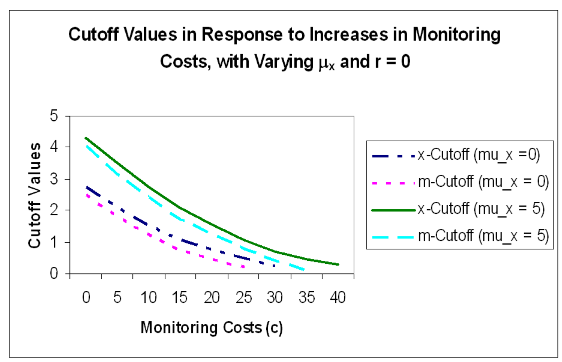
(a)



(b)



(c)



(d)

Figure 15: Cutoff Value Behavior in Response to Increases in Monitoring Costs

represents some type of monitoring cost, or transparency level associated with a particular organization, then it does not immediately make sense that a donor will decrease his first stage cutoff criteria in the face of increasing costs (i.e. why would a donor set the bar lower to sample an organization if the cost to do so is greater?). An important distinction to be made is that the cost in this context is not an explicit per period search cost (this cost is effectively none), but instead it is the cost to sample a given organization, and is only paid if the donor chooses to do so within a period. The model could be amended such that a per period search cost is included in addition to the the sample cost, however the analysis still stands with or without the inclusion. If, on average, it costs more to sample each organization that one encounters throughout the process, it in turn becomes more costly everytime one donates and later finds out that the organization was not a good match for him. Thus, on a surface level, it would seem as though one may want a larger spread between s and c (i.e. higher cutoff value) to induce them to donate, with the thought that the true value of the match may be more to their liking once revealed in the second period. To understand why the first stage cutoff value, $\bar{m}$, decreases in the face of increasing monitoring costs it helps to first consider a more basic search model.[23]

If one considers the canonical job search model in which a worker searches each period, at a cost c, for a job offer with associated wage w, then the donor's response to increases in expected cost can be better understood. The simple job search example strips away several components of the donor search model, but is useful for expository purposes. The optimal search policy in the job search model is known, like the presented model, to have a reservation wage policy as the optimal policy, and more importantly the policy can be solved for myopically. In this sense the optimal reservation wage is the wage that makes the *marginal cost of obtaining exactly one more job offer = expected marginal return of one more offer*, which can represented

[23]A similar argument can be made for why $\bar{x}$ decreases

by (73).

$$c = \int_{w^{res}}^{\infty} (x' - w^{res}) dF(x') \tag{73}$$

The left-hand side represents the cost of gaining one additional offer, and the right-hand side represents the expected gain from the next offer. w^{res} is the wage offer that makes these two sides equal. In other words, a worker currently holding offer w^{res} in hand would be indifferent between accepting the current offer, and searching one more time for another offer. Wage offers less than w^{res} would induce the worker to continue searching, and wage offers greater than w^{res} would prompt the worker to halt his search. $F(x')$ is the cumulative distribution of wage offers, and so $E[x'] = \int_{-\infty}^{\infty} x' dF(x')$. Consequently, it can be shown that if the distribution of the wage offers stays the same, but c increases, then w^{res} will decrease. This can be understood by considering that as the cost of search increases, then the expected marginal return of one more offer must increase, via w^{res} to satisfy (73). Given that the distribution is constant, the way to increase the expected return is to decrease w^{res}. The presented donor search model can be analogously applied to understand why an increase in the monitoring cost causes a decrease in the first stage cutoff value, $\bar{m}$.

In the donor search model there is no explicitly defined search cost, such that the donor must pay some cost simply to proceed from period to period, so in this instance $c_{search} = 0$. However, there is β which takes on a similar role of c_{search} by making it costly for the donor to continue to search via the discounting of future payoffs. Although there are several significant deviations from the job search example, it still holds that an optimal first stage cutoff policy can be described via a cutoff policy, defined such that the cost of one additional organization introduction is equivalent to the expected payoff from one additional organization discovered. Through some abuse of notation and abstraction from the more structured donor search model, equation (74) represents the myopic condition around which a donor will base his cutoff decision, $\bar{m}$.

$$0 = \beta E \max\{r - \bar{m}, \int_{\bar{m}}^{\infty} (m' - \bar{m}) dF(m')\} \tag{74}$$

Again, the left-hand side represents the cost of finding one additional organization, while the right-hand side represents the expected marginal payoff from continuing to search one more period. $\bar{m}$ is the cutoff value that satisfies (74). The influence of the reservation payoff, r, will be ignored for now and the assumption is made that $\int_{\bar{m}}^{\infty} (m' - \bar{m}) dF(m')$ will dominate the expression. Remembering that m is derived from the values of s and c for a particular organization the expression is expanded to (75), where $F(s')$ and $F(c')$ are the cumulative distributions of s and c respectively.

$$0 = \beta \left[\int_{\bar{s}}^{\infty} \int_{\bar{c}}^{\infty} ((s' - c') - (\bar{s} - \bar{c})) dF(s') dF(c') \right] \tag{75}$$

On the right-hand side the first half of the expression represents the marginal expected payoff, via s, for one more search period. The second half of the expression represents the expected marginal monitoring cost, c. The combination of the two expressions are equivalent to $\int_{\bar{m}}^{\infty} (m' - \bar{m}) dF(m')$, but allows one to better understand the effects of each component on $\bar{m}$. From here it can be seen that if all other factors are held constant, while $E[c']$ increases, and assuming that $\bar{s}$ is fixed, then it becomes clear that $\bar{c}$ must increase in order to compensate for the increase, such that (75) remains in balance. However,this increase in $\bar{c}$ leads to a decrease in $\bar{m}$, which is the observed effect from the parameter analysis. While it is not clear exactly how $\bar{s}$ and $\bar{c}$ will adjust internally, if one returns back to the aggregate level then it becomes clear that as $E[c']$ increases, then the $E[m']$ decreases, which will require a further decrease in $\bar{m}$ if (74) is to hold where $c_{search} = 0$. Simulation results presented in the next section will enlighten the understanding of how s and c behave in this context.

Equation (74) can also be used to understand the effect of r on cutoff values. r was observed earlier to have the effect of increasing cutoff values, and it can be understood

Table 3: Dispersion in Monitoring Costs

Scenario	Cost Distributions	Set of Cost Values	$\bar{m}$	$\bar{x}$
1	$\{.5, .5\}$	$\{0, 20\}$	1.577	1.890
2	$\{.333, .333, .333\}$	$\{0, 10, 20\}$	0.936	1.242
3	$\{.25, .25, .25, .25\}$	$\{0, 6.667, 13.333, 20\}$	0.613	0.907
4	$\{.20, .20, .20, .20, .20\}$	$\{0, 5, 10, 15, 20\}$	0.356	0.694

that this is a result of a donor simply having more competitive investments for his money, and thus he would need to be assured of achieving a higher payoff from donation as r increases.

The second component of the cost analysis deals with the the effect of the cost distribution, or dispersion, on the cutoff values. The preceding analysis assumed a trivial distribution by making the assumption that there existed a universal monitoring cost for all organizations. This analysis looks at the effect of presenting the donor with a non-trivial distribution of cost values. The analysis considers several scenarios, as outlined in Table 3, beginning with a bi-level cost structure of $Prob\{c = 0\} = 0.5$ and $Prob\{c = 20\} = 0.5$, and progressively subdivides the scenarios from that point.

Table 3 shows that as the cost structure becomes more segmented (within a defined interval) the cutoff values decrease. This can be interpreted as more variety within the market induces increased first stage sampling.

3.4.1.3 Mean Analysis

The mean analysis focuses on the effect of variations of the value μ_x on the observed cutoff values. Figure (16) shows that the requisite cutoff values increase with μ_x. This comes directly from the fact that as μ_x increases the standard by which all organizations are judged must increase. To compensate for the system shift, an individual donor must alter the criteria by which it judges an organization.

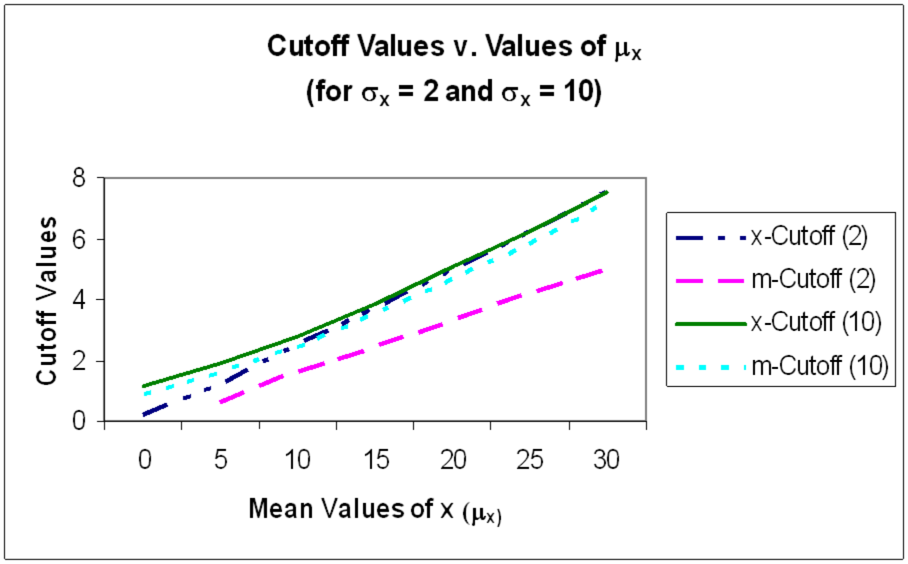


Figure 16: Change in Cutoff Values in Response to Changes in μ_x

3.4.1.4 Variance Analysis

The variance analysis focuses on the effect of variations of the value σ_x on the observed cutoff values, and shows via figure (17) that the cutoff values increase with σ_x.

3.4.2 Donor Search Results

The second stage of the simulation process approaches the question of how the market functions within certain constructs, and provides predictive results, given assumptions about donor behavior. Several scenarios are constructed, around which analysis as it relates to anticipated donor behavior can be made. This is begun with the baseline case (ψ_{base}) outlined in the preceding section. For the vector defined by ψ_{base} the first stage was repeated over several iterations, and an average of the cutoff values ($\bar{x} = 1.8921, \bar{m} = 1.6056$) was used as input into the second stage simulation. There are several metrics of the market structure and donor behavior that can be captured

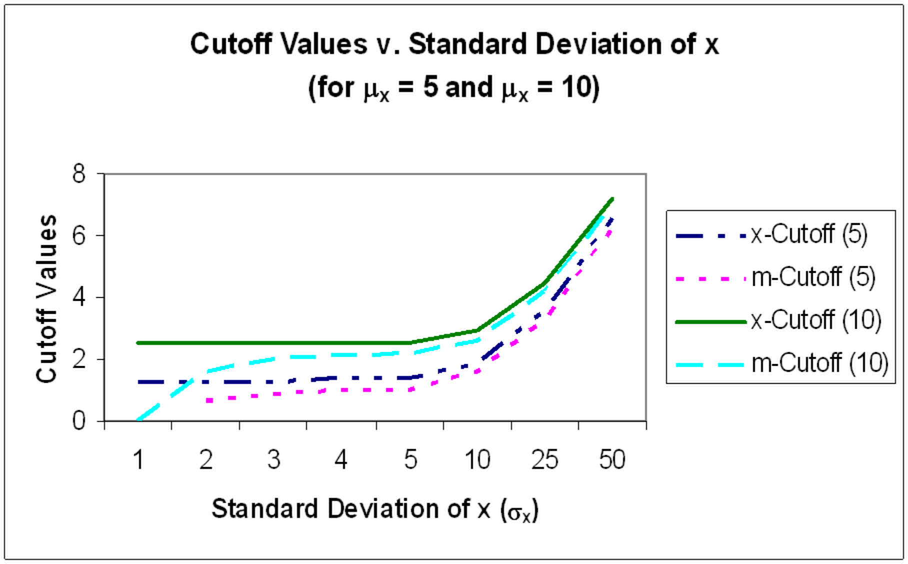


Figure 17: Change in Cutoff Values in Response to Changes in σ_x

via simulation, and which are considered within the course of discussion.

As in the preceding section, the simulation takes a standard input vector of operational parameters. In addition to the previously described parameters the second stage must also use the input vector,

$$\gamma = (N, M, T, distExp, orgCost), \tag{76}$$

where N, M, and T are as previously described. $distExp$ establishes the exposure distribution over each organization ($Prob\{\text{Organization } j \text{ is selected by a donor } i\}$), and $orgCost$ assigns a cost value to each organization in accordance with $cDist$ and $cSet$ defined previously. The input vectors ψ and γ link the first and second stages of the simulation, and together define an entire scenario. For the baseline scenario, γ_{base} is defined by,

Table 4: Baseline Organization Parameters

Organization	Exposure Probability	Monitoring Cost
1	10	0
2	20	5
3	30	0
4	40	5

$$\gamma_{base} = (10, 4, 100, \{10, 20, 30, 40\}, \{0, 5, 0, 5\}). \tag{77}$$

In this particular scenario there are 4 charitable organizations, with the structure defined in table (4).

Defined in this way Organization 4 has a higher probability of discovery than Organization 3, but also has a higher monitoring cost. Running the simulation and analyzing the outputs allows for a better understanding of the tradeoff between the two parameters.

Each iteration of the simulation generates the number of donors that made contributions to each organization. For a given scenario, in order to provide an appropriate approximation of the average number of donations each organization receives, a requisite number of replications must conducted. As can be seen in figure (18), for Organization 2, as the number of scenario iterations increases the expected number of donations provided to the organization stabilizes around 57.1 in accordance with strong law of large numbers (SLLN). In particular, the convergence seems to happen rather quickly around the 50 iteration mark.

As an initial analysis two simulation replications scenarios were run. One scenario with 50 replications of the baseline case, and another with 500 replications. The output from the scenarios can be found in tables (5) and (6). The output provided via both scenarios shows that on average Organization 3 will receive more donations than 4. Thus, while Organization 4 has a higher likelihood of being viewed by a prospective donor, the fact that it is less transparent (i.e. harder to monitor) than

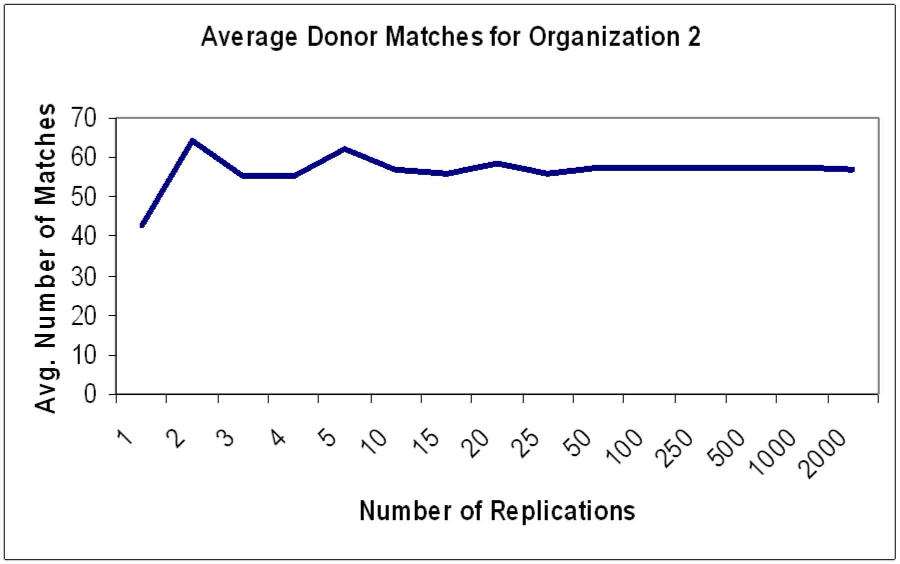


Figure 18: The Average Number of Donations to Organization 2 over Increasing Replications

Organization 3 leads to less donations. While seemingly suggestive that exposure levels may be more influential than transparency levels in determining market share, at least in the defined proportions, an analysis of the Organization 1 and 2 pair seems to suggest the opposite. More testing is needed to better characterize the relationship between transparency and exposure. However, before preceding with the analysis it will be necessary to more explicitly define what is meant by the terms "market size" and "market share," within the context of this simulation analysis.

The way the analysis is currently structured, it is such that each simulation is initiated with N donors and M organizations in the market. The number of donors in the market at any one time is static (i.e. always N), and is such that for each period all donors who form a 2nd stage match with an organization are removed from the system and replaced with new donors. In this sense, N in each period is equivalent to

Table 5: Baseline Output (50 Replications)

	Org1	Org2	Org3	Org4
Sample Mean	40.1	58.6	118.94	113.9
Sample Variance	54.6225	59.1020	98.9555	84.949
Skewness	0.3984	0.4299	-0.6817	-0.3544
α	0.05	0.05	0.05	0.05
C.I.	±2.0994	±2.183784	±2.8257	±2.6181

Table 6: Baseline Output (500 Replications)

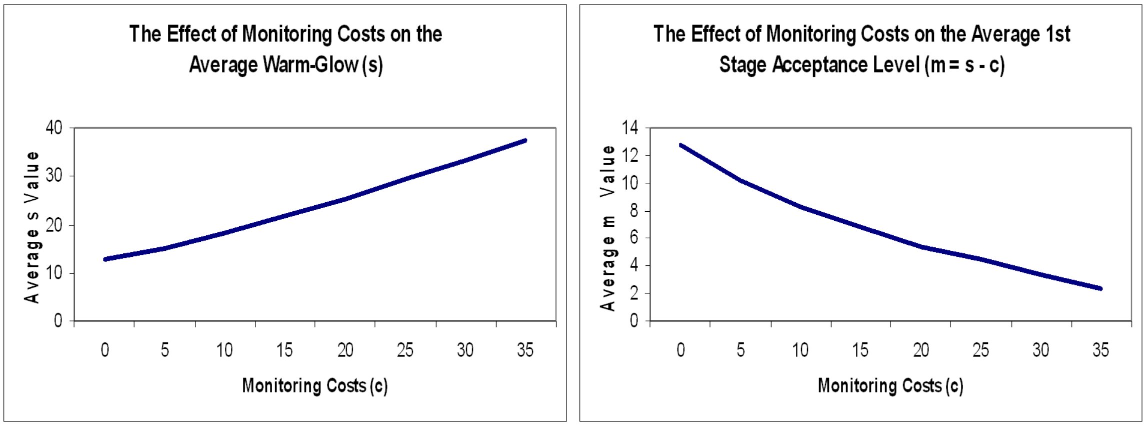
	Org1	Org2	Org3	Org4
Sample Mean	40.2	57.596	119.79	115.218
Sample Variance	33.9848	50.2813	92.8476	86.7119
Skewness	0.0639	0.1213	-0.0443	0.0337
α	0.05	0.05	0.05	0.05
C.I.	±0.5122	±0.623	±0.8466	±0.8181

$$N^t = N^{t-1}_{\text{Matched Donors}} + N^t_{\text{New Donors}}. \tag{78}$$

While the number of donors within the market in any period t is constant, the number of donors that enter and leave the market over a defined period will vary in accordance with donor behavior. In this respect if donor search time, on average, is low then there be a larger turnover in donors during the T interval. The number of donors that leave the system over a defined interval is considered to be a proxy of the market size in this context. The market share of a particular organization is subsequently defined as the number of donors that chose to give to its organization during the defined period. The market metrics, defined as such, allow one to better understand the effects of parameter manipulation within the marketplace.

3.4.2.1 Monitoring Costs Effects on Search Behavior

We begin with an analysis of how the monitoring cost effects the charitable giving market, particularly as it regards the number of donors who enter the market, average donor search time, and the average warm-glow values observed.



(a) (b)

Figure 19: Monitoring Cost Effect on Average m and s Values of Matched Donors

In 3.4.1.2 it was noted that the cutoff values for both the 1st and 2nd stage were decreasing in the cost when it was kept uniform across all considered organizations. It was conjectured that although cutoff values were decreasing, the actual level of warm-glow, s, captured by a donor might be increasing. Figure (19a) shows that, in fact, as the cost increases the average s value over the set of matched donors increases linearly. As a response to this, Figure (19b) shows that the average $m = s - c$ decreases in the uniform cost, which shows that the magnitude of the cost increase is greater than the change it induces in the average requisite warm-glow value for a match.

An extension of this analysis is the observation that uniform increases in the monitoring cost severely inhibit donor participation in the market. Figure (20) offers insight into this statement as it can be seen that as cost increases there is a rather dramatic increase in the time it takes the initial set of donors to find a matching organization.[24] As a complementary metric, it can be seen that the average donor search time is also increasing rather significantly over cost increases.

In a similar way, the segmentation of the monitoring cost structure, and its effect on the cutoff values was also considered. Increased segmentation in the cost structure

[24]Search time is defined as the number of periods that a donor stays in the market until it is matched, and leaves.

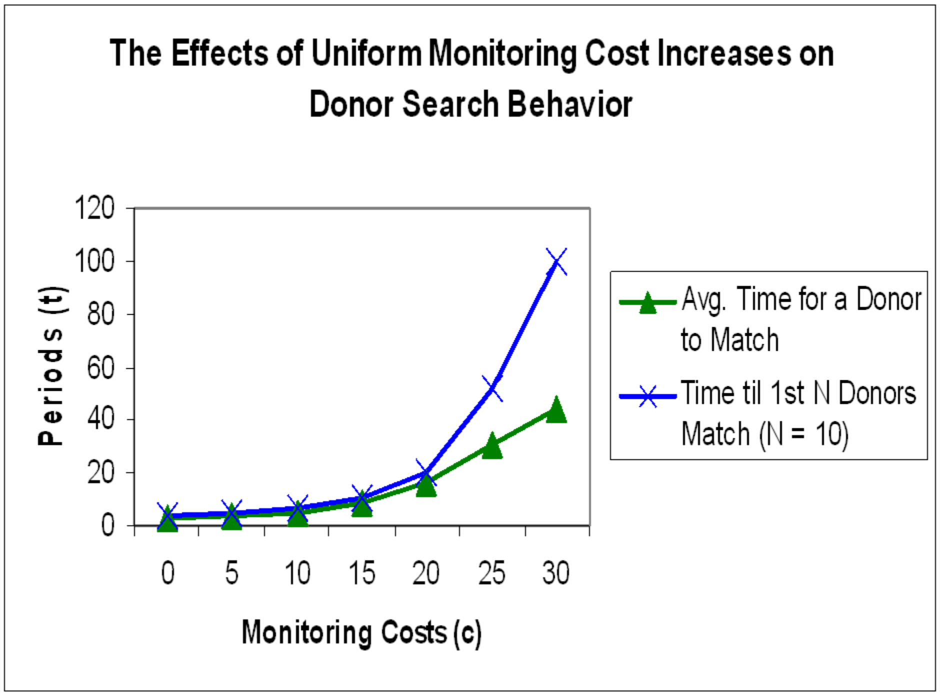


Figure 20: The Effect of Monitoring Costs on Donor Search Time

caused the 1st and 2nd stage cutoff values to decrease. The underlying simulation statistics in response to increases in segmentation help to provide a better picture of its effect on search behavior and market outcomes. Figure (21) provides an analysis of the average s and m values as segmentation increases. Considering the defined scenarios in Table 3 it is easily seen that an increase in segmentation leads to an increase in average s values realized by matched donors, and a decrease in the average m values. Given that $E[c] = 10$ in each scenario, the changes in market structure can be attributable to the number of transparency segments available within the market. However, while the cutoff levels change, Table 7 suggests that the underlying market structure is not effected significantly.[25] In fact, the market size remains virtually constant across the segmentation levels. This is in contrast to the market size that

[25]The Average Views per Match is defined as the number of organizations that a donor saw before he matched with a particular organization.

results from increasing $E[c]$, which also leads to decreasing cutoff values.

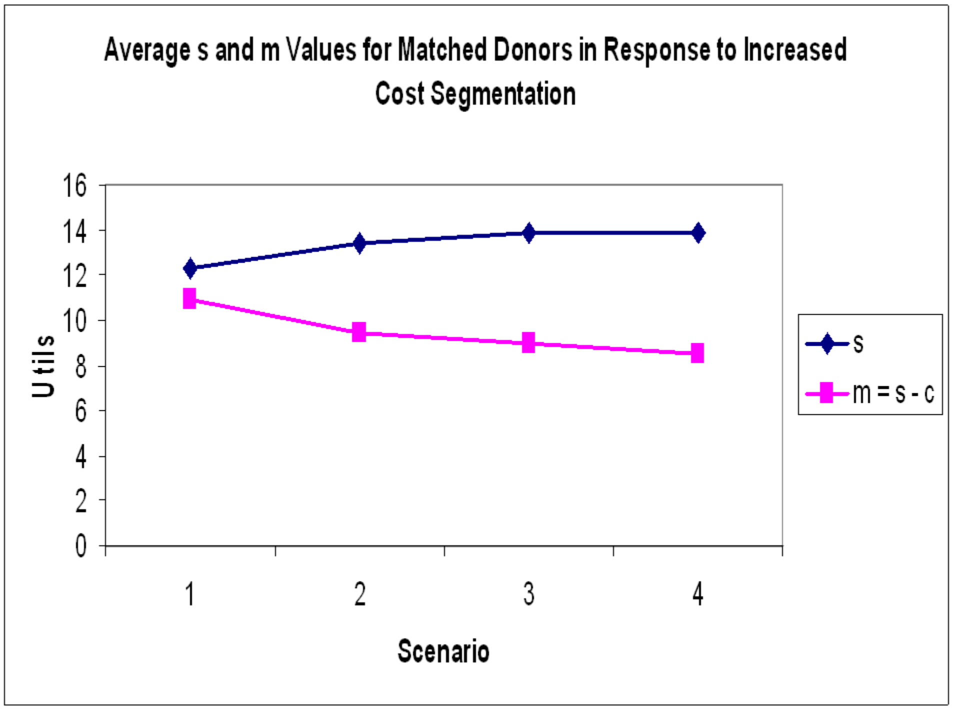


Figure 21: The Effect of the Segmented Monitoring Costs on the Average 1st Stage Acceptance Level (m = s-c) and Warm Glow (s)

Table 7: Cost Segmentation Effects on Donor Search Behavior

Scenario	Avg. Views per Match	Avg. Time to Match	Time til 1st N Match
1	2.936	4.006	5.06
2	3.046	4.108	5.28
3	3.016	4.073	5.05
4	2.949	4.002	5.05

3.4.2.2 Cost Effects on Market Structure

While the donor search behavior is important in itself, its relation to the charitable marketplace, and how it changes in response to organization behavior is of primary importance in considering organization behavior. This section considers the effect of changes in the cost for one organization, or sector, relative to others, so that trade-offs can be better understood. Section 3.3.3 lays out an argument that monitoring costs, and by extension transparency, are important via the role they play in the donor decision process. Consequently, the notion is put forth that organizations will undertake activities to decrease their costs (increase transparency) relative to others, even perhaps if the activities are not wholly aligned with their organizational goals. The extent to which this is likely to be true will be correlated with the expected benefits from such behavior. Specific effects of unilateral cost changes by an individual organization are examined here.

To examine this issue, the effect of both unilateral cost increases, and cost decreases were considered. The effects of cost increases and decreases by individual organizations on the size of the market are outlined in Figure (22), and effects on the market share captured by an individual organization are shown in Figure (23).

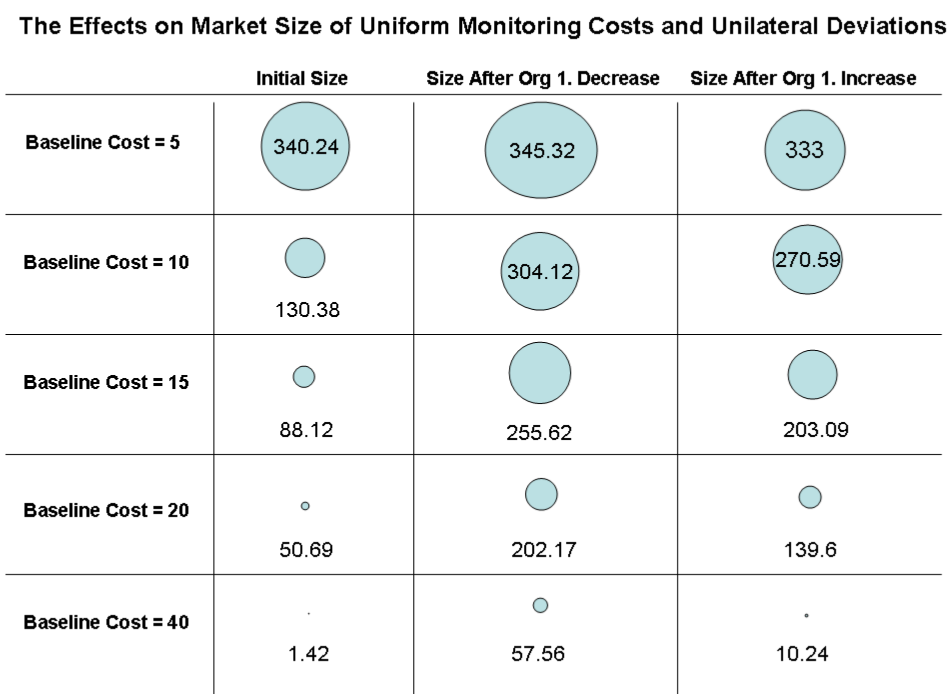


Figure 22: Effects on Market Size of Monitoring Cost Deviations

Figure (22) was derived by considering five baseline cost scenarios, of 5, 10, 15, 20, and 40. After each scenario was run for the baseline case, in which exposure

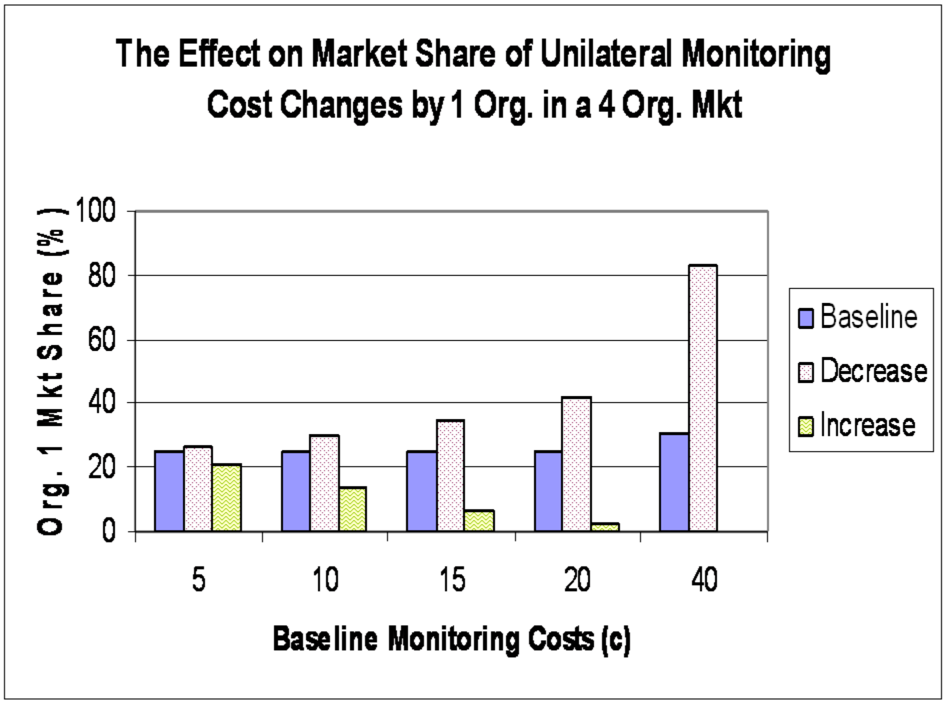


Figure 23: Effects on Organization Market Share of Monitoring Cost Deviations

levels and costs were uniform across a set of 4 organizations, the monitoring costs for Organization 1 was decreased by half, and the scenario was rerun. The same was done for a 50% increase in the monitoring costs associated with Organization 1. Figure (22) outlines the market size generated in each scenario over a defined period of T = 100. It can be seen that the effect of increases and decreases in cost (decreases and increases in transparency) is highly dependent on the initial state of the market. In particular, if the overall transparency level of the organizations within a given market are already very good, then the deviation by one organization one way or the other does not have a significant effect on the overall market structure.

Similarly, it can also be seen that the individual market share is also dependent on the overall state of transparency within a market. Figure(23) shows the market share that Organization 1 is able to capture in all three scenarios for a given baseline cost structure. In the case of a baseline level of 5, a 50% increase or decrease in transparency relative to the rest of the market has a neglible effect on the share of donors the organization is able to capture. However, in the case of a baseline level cost of 40 (i.e. a relatively non-transparent market), investment in transparency improvements of 50% lead to an almost 60% increase in market share. How these results align with the effects of increases in exposure levels are considered next.

3.4.2.3 Exposure Sensitivity

The effect of exposure on an organization is investigated here by holding constant the effects of transparency on market outcomes. In this instance, a baseline scenario is once again created, wherein 4 organizations within a given market are assumed. Initially, each organization has an equal chance of being discovered by a perspective donor (namely a 25% chance). From this point, keeping all other exposure levels uniform, the first organization's exposure probability is increased such that it a has higher chance of discovery by perspective donors. Figure (24) shows that the market share captured by the first organization linearly increases in exposure level. However, while cost effects were able to increase or decrease market share, exposure, because it is assumed to be rivalrous, only redistributes donors, and does not expand or reduce the market.

Considered within the context of the leading example, it is clear that there are significant implications both from an organization and market standpoint as it regards changes in behavior by organizations. Section (3.5) considers these issues within the context of charitable organization behavior.

3.5 Implications on Organization Behavior and Markets

This chapter began with an introductory assumption that charitable organizations will act strategically to obtain funds from donors, even if it means drifting from their core mission at some level. The extent to which this hypothesis can be supported or rejected is a function of both organization priorities, and donor behavior. Assuming

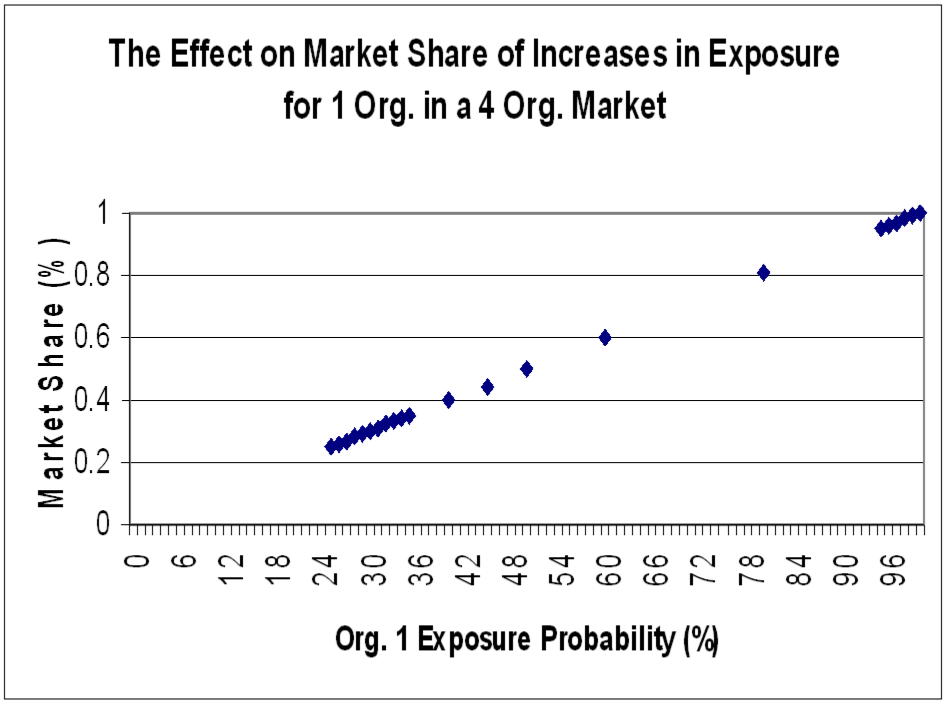


Figure 24

that donor decision making is in part shaped by how well a donor is able to ascertain the value of their contribution to an organization, and how easily they are able to find a given organization, the presented search model allows one to characterize donor behavior in response to posited market scenarios. From this perspective a given organization is able to ascertain what the payoff would be, in terms of market share, of unilateral deviation along one of these metrics. Whether or not these payoffs are enough to alter organization behavior is dependent upon a given organization's objective function, and how closely aligned are the payoff inducing behaviors with its mission.

Table 8 considers potential activities or strategies that an organization can undertake to increase either transparency, exposure, or both. Each of these activities is costly to the organization in some sense as it may divert physical and monetary resources from core objectives. The extent to which each activity is *worth it* from

Table 8: Transparency and Exposure Increasing Activities

Transparency Activites	**Exposure Activities**
Newsletters	Ad Campaigns
Videos and Pictures	Awareness Raising Events
Donor Site Visits	Participation in "Hot Spots"
Social Media	Celebrity Endorsements
Work in easily Viewable Areas	
Independent Audits	

the perspective of the organization has to be considered within the context of the current state of that organization's market or sector, as the payoff has been shown to be largely dependent on the the relative transparency levels of other market participants. However, the payoff from unilateral exposure increasing activities, while perhaps harder to execute on a sustained basis, appear to yield gains that are less dependent on the market. Depending on how closely aligned these activities are to an organization's core mission, in particular as it regards participating in certain "hot spots," or areas of the humanitarian market which receive large amounts of attention, an organization's pursuit of these activities can result in waste and inefficiency as it regards the use of resources. As an example consider the relief environments of the previous chapter.

Within the context of humanitarian relief organizations the preceding chapter posited, based on anecdotal evidence, that high publicity relief areas tend to initially attract an excess of resources and organizations, as organizations use the event as an opportunity to signal their quality to potential donors. Implicit within the quality signal is an increase in organization transparency, real or otherwise, that allows a donor to more readily view the work of that organization, as it occurs within a media saturated environment. Furthermore, as a result of the high visibility level of the opportunity, organizations become more exposed from the standpoint of discovery by potential donors. In this context the simultaneous increase in exposure and transparency, even if only for a brief period, presumably allows an organization to increase its donor attraction.[26] The signaling model from the previous chapter provides some guidance as to how a donor might make a tradeoff decision in this context.

Furthermore, aside from individual organization behavior, the results of the search model bolster an argument for increased transparency and regulation of non-profit related organizations across the board. The model argues that markets with high monitoring costs effectively shut out potential donors. This is exceedingly important, as an increase in the donor base can lead to increased provision of necessary services. Along these lines it should be considered that the model is also applicable to sectors within the philanthropic marketplace. Much of the discussion has centered around the consideration of individual organization behavior. However, these transparency and exposure levels can be endemic to a particular sector, and can be used to explain why one charitable cause may command a larger segment of the market than another.

3.6 Conclusions

At its core, this chapter builds on Jovanovic's model of job search to construct a model of how donor's search for charitable organizations to contribute funds toward. The model is constructed around the notion that a donor's decision process, in addition to his innate preferences, is guided by organization transparency and exposure levels. Furthermore, the model is developed, in part, to offer an explanation for why organizations may engage in publicity seeking behavior as it regards which causes and activities they choose to participate in. To this extent, the model incorporates measures of transparency, via monitoring costs, and exposure into a functional two-stage donor search framework, and allows for one to predict behavior in response to

[26] It should be noted that the argument, at least in this instance, is not that organizations create the increased exposure and transparency, but that they take advantage of an opportunity for which these dimensions are increased via participation because of the characteristics of the event.

various market constructions. Furthermore, if it can be verified that the presented model is indeed a reliable predictor of behavior it can be used to define markets or organizations to yield desired results as it regards donor participation.

Perhaps the most informative result of the model is in regards to the effect of transparency on the overall market structure and on the individual organization. While increases or decreases in exposure levels by individual organizations altered their market share, it did nothing to effectively alter the level of donor participation within the market overall. Conversely, increases and decreases in monitoring costs altered the overall market structure. It was shown that the more transparent the market as a whole, the larger the donor pool became, and the harder it became for an organization to distinguish itself along this metric. In particular, section 3.4.2.2 showed that the returns to increases in transparency for a given organization were almost negligible if the market was already fairly transparent. However, for markets with high monitoring costs initially, the increase in transparency of the same magnitude as in high transparency markets yielded a much larger share of the donor pool, while also increasing the overall market size. Section 3.5 discussed the implications for this as it regards organization decision making in resource placement. In addition to helping answer questions proposed at the outset, the model also raises several questions, along with opening the door for extensions in future work.

Questions of the empirical variety consider how one might measure the transparency of a particular organization, or sector, within the humanitarian marketplace, in practice. Subsequently, it is then worth considering how transparency varies across organizations and sectors, and whether or not there is any difference in funding levels which would lead one to conclude that transparency is indeed a sufficient predictor of how donors will allocate their funds.

There are several extensions to the model which were not considered within this chapter, but would be useful to consider in future work. As of now the organization behavior is exogenously defined via the cost and exposure distribution constructs. An extension of the model to an environment in which organizations can engage in real-time adjustment of these parameters would add increased depth to the model, and provide further insight into organization behavior.

In the same vein as endogenous modeling, the model could be extended to consider questions of "mission drift" within the humanitarian marketplace. In particular, if the model is extended to observe dynamic organization behavior over a sustained interval, then the model could be used to classify or predict mission drift [37], and how it might occur as a result of a defined market structure.[27]

Another considered extension is that of a two-sided search model. As currently defined the model is a one-sided matching model in which the donor picks an organization to match with, and the organization always accepts the match (i.e. the organization never refuses funding). However, if one considers a market construction in which donors are allowed to earmark their funds to certain organizations, for specific causes, then the donor may be refused by organizations that are not interested in accepting earmarked funds. The extent to which this alters the model is a worthwhile consideration given the recent trend in allowing for earmarked donations within the charitable giving arena.

In chapter 4, the organization under consideration offers the donor a money back guarantee on his investment if he is not satisfied with the outcomes. Such a guarantee would presumably alter donor behavior, perhaps increasing their initial warm-glow value, effectively decreasing his first stage cutoff value. However, inclusion, and serious modeling of this money back guarantee in the donor's value function when he encounters specific organizations would be a credible extension to the model, and would offer a direct comparison to the cases in which one was not offered.

[27] "Mission drift" is a term used consider how far an organization's portfolio of activities has strayed, or drifted, away from its core mission.

While the extensions will help to advance the understanding of how charitable marketplaces work, the extent to which the model is useful, is based in large part on the validity of the assumptions made at the beginning. In particular, the assumptions as it regards the effect of transparency and exposure on donor decision making. Chapter 4 uses donor data from an online charitable marketplace to consider, empirically, to what extent these attributes matter, as it regards donor decision making. The model implies that beyond a certain market transparency level increases or decreases by individual organizations within the marketplace have a negligible effect on decision making, Chapter 4 provides insight into whether or not this can indeed be the case.

3.7 Appendix A: Existence and Solution

To begin with, the problem space is collapsed such that $J(x)$, $V(m)$, and Q can be incorporated into a single value function. Remembering that, $V(m) = \max\{m + \beta \int J(x)dF(x|s), r + \beta Q\}$, allows for the substitution of $J(x)$ and Q.

$$V(m) = \max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta Q]dF(x|s), r + \beta Q\} \tag{79}$$

$$\begin{aligned} &V(m) = \\ &\max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int V(m')f(c')dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)]dF(x|s), \\ &r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int V(m')f(c')dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\} \end{aligned} \tag{80}$$

Where, $m' = s' - c'$.

A metric space $(C[0, m_B], d_\infty)$ is defined, along with an operator T on the right hand side of (80), which maps continuous functions V into functions TV, such that (80) can be written as $V = TV$. It is assumed that m has a cumulative distribution function such that for m_t in period t, $Prob\{m_t \leq m\} = F(m)$ where $F(0) = 0$ and $F(m_B) = 1$. Below, T is shown to be a contraction through satisfaction of Blackwell's sufficiency conditions. If T is a contraction, it follows that there exists a unique continuous solution to the functional relation $TV = V$.

Blackwell's Sufficiency Conditions:

Monotonicity

To show monotonicity, it should be that for $\nu(m) \geq w(m)$, then $(T\nu)(m) \geq (Tw)(m)$.

$$
\begin{aligned}
&(T\nu)(m) = \\
&\max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int \nu(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)] dF(x|s), \\
&r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int \nu(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\} \\
&\leq \max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int w(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)] dF(x|s), \\
&r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int w(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\} = (Tw)(m)
\end{aligned}
\tag{81}
$$

Discounting

Let a denote a function that is constant at the real value a for all points in the domain $C[0, m_B]$. For any positive real a and every $C[0, m_B]$, if T is a contraction, it must be that $T(\nu + c) \leq T(\nu) + \beta a$ for some β satisfying $0 \leq \beta < 1$.

$$
\begin{aligned}
&T(\nu + a) = \\
&\max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int (\nu(m') + a) f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)] dF(x|s), \\
&r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int (\nu(m') + a) f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\}
\end{aligned}
\tag{82}
$$

Consider:

$$
r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int (\nu(m') + a) f(c') dG(s'|\cdot) = r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int \nu(m') f(c') dG(s'|\cdot) + \beta a \tag{83}
$$

Which yields:

$$\max\{m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)]dF(x|s),$$
$$r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)\}$$
$$\leq \max\{m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)]dF(x|s),$$
$$r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int \nu(m')f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)\}+\beta a \tag{84}$$

Alternatively, consider:

$$m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\cdot)]dF(x|s)$$
$$=m+\beta\int \max[\frac{x}{1-\beta}, r+\beta a+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int \nu(m')f(c')dG(s'|\cdot)]dF(x|s)$$
$$\leq m+\beta\int (\max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int \nu(m')f(c')dG(s'|\cdot)]+\beta a)dF(x|s)$$
$$=m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int \nu(m')f(c')dG(s'|\cdot)]dF(x|s)+\beta^2 a \tag{85}$$

Which yields,

$$\max\{m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)]dF(x|s),$$
$$r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)\}$$
$$\leq \max\{m+\beta\int \max[\frac{x}{1-\beta}, r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int \nu(m')f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)]dF(x|s),$$
$$r+\beta\sum_{c'=\underline{c}}^{\bar{c}}\int (\nu(m')+a)f(c')dG(s'|\mu_x+\mu_\epsilon,\sigma_x^2+\sigma_\epsilon^2)\}+\beta^2 \tag{86}$$

Then, considering (84) and (86), it must follow that.

$$T(\nu + a) =$$

$$\max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int (\nu(m') + a) f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)] dF(x|s),$$

$$r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int (\nu(m') + a) f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\}$$

$$\leq \max\{m + \beta \int \max[\frac{x}{1-\beta}, r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int \nu(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)] dF(x|s),$$

$$r + \beta \sum_{c'=\underline{c}}^{\bar{c}} \int \nu(m') f(c') dG(s'|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2)\} + \beta a = (T\nu) + \beta a \tag{87}$$

Consequently, it is established that T is a contraction mapping with modulus β.

3.8 *Appendix B: Value Function Iteration*

Given the following equations, and satisfaction of Blackwell's sufficiency conditions as outlined in Appendix A, such that a fixed point solution is guaranteed to exist, one can solve for the value functions by iterating over increasingly better guesses for the value of Q.

Let the worker's belief about the distribution of x, given $s = x + \epsilon$ be given by $N(\mathrm{E}[x|s], \sigma_1^2)$, where $\mathrm{E}[x|s] = \mu_x + K_x(s - (\mu_x + \mu_\epsilon))$, and $\sigma_1^2 = \mathrm{E}[(x - \mathrm{E}[x|s])^2|s] = K_x\sigma_\epsilon^2$, with $K_x = \frac{\sigma_x^2}{\sigma_x^2+\sigma_\epsilon^2}$.

$$J(x) = \max\{x + \beta J(x), r + \beta Q\} \tag{88}$$

$$V(s-c) = \max\{s - c + \beta \int J(x) dF(x|s), r + \beta Q\} \tag{89}$$

$$Q = \sum_{c=\underline{c}}^{\bar{c}} \int V(s-c) f(c) dG(s|\mu_x + \mu_\epsilon, \sigma_x^2 + \sigma_\epsilon^2) \tag{90}$$

To arrive at a solution (e.g. values for each value function) the fixed point property of the system of functions can be exploited by iterating over (88),(89), and (90), in the following manner:

a. Guess a value for Q, let the guessed value be Q^i with i = 1.

b. Given Q^i, compute sequentially the value of $J^i(x)$, $V^i(m)$.

c. Given solutions to $J^i(x)$ and $V^i(m)$, calculate an updated Q^i called $\tilde{Q}^i$.

d. Let $Q^{(i+1)} = \tilde{Q}^i$ (some other scheme can be used to update $Q^{(i+1)}$, such as $Q^{(i+1)} = gQ^i + (1-g)\tilde{Q}^i$, where $g \in (0,1)$.

e. Iterate until convergence.

3.9 Appendix C: Kalman Filtering

The Kalman filter is a recursive algorithm for computing the expectation of an unobserved vector, conditional upon an observed noisy vector. In the context of this paper, x is the unobserved vector, and s is the noisy observed vector. Given that s is defined via x, as $s = x + \epsilon$ the expectation of x can be updated from E$[x]$ to E$[x|s]$ upon the observation of s. The Kalman filter can be used to recursively determine $\hat{x} = \mathrm{E}[x|s]$. Below, the application of the Kalman filter to a generic linear state space system is defined, and then translated to the problem presented in this paper. This is largely adapted from Ljungqvist and Sargent [56].

Given x_0, let

$$x_{t+1} = Ax_t + Cw_{t+1} \tag{91}$$

$$y_t = Gx_t + \nu_t \tag{92}$$

where x_t is an (n x 1) state vector, w_t is an i.i.d. sequence Gaussian vector with $Ew_t w_t' = I$, and ν_t is an i.i.d. Gaussian vector orthogonal to w_s for all t, s

with $Ev_tv_t' = R$; and A,C, and G are matrices conformable to the vectors they multiply. Assume that the initial condition x_0 is unobserved , but is known to have a Gaussian distribution with mean $\hat{x}_0$ and covariance matrix Σ_0. At time t, the history of observations $y^t \equiv [y_t, \ldots, y_0]$ is available to estimate the location of x_t and the location of x_{t+1}. The Kalman algorithm is

$$\hat{x}_{t+1} = (A - K_tG)\hat{x}_t + K_ty_t \tag{93}$$

where

$$K_t = A\Sigma_tG'(G\Sigma_tG' + R)^{-1} \tag{94}$$

$$\Sigma_{t+1} = A\Sigma_tA' + CC' - A\Sigma_tG'(G\Sigma_tG' + R)^{-1}G\Sigma_tA \tag{95}$$

$\Sigma_t = E(x_t - \hat{x}_t)(x_t - \hat{x}_t)'$, and K_t is called the Kalman gain.

Equivalently, the Kalman filter is sometimes written as the "observer system"

$$\hat{x}_{t+1} = A\hat{x}_t + K_ta_t \tag{96}$$

$$y_t = G\hat{x}_t + a_t \tag{97}$$

where $a_t \equiv y_t - G\hat{x}_t \equiv y_t - \mathrm{E}[y_t|y^{t-1}]$.

Assuming a 2-stage process where $t = 0$ denotes the the initial stage, and $t = 1$ denotes the second stage, equation (93) can be defined as

$$\hat{x}_1 = (A - K_0G)\hat{x}_0 + K_0y_0 \tag{98}$$

where $\hat{x}_1$ denotes the mathematical expectation of x in the second stage given the first stage observation of y_0, and unconditional first stage expectation $\hat{x}_0 = \mathrm{E}[x_0]$. Similarly, Σ_1 is the second stage covariance, as defined via first stage parameters.

By letting $A = 1$, $C = 0$, and $G = 1$ the presented modified Jovanovic model can be written as a linear state space analog to equations (91) and (92) as defined by (99) and (100).

$$x_{t+1} = x_t \tag{99}$$

$$s_t = x_t + \epsilon_t \tag{100}$$

Consequently s_t is a noisy signal defined by x_t and ϵ_t, and $x_{t+1} = x_t$. x_t and ϵ_t are distributed by $N(\mu_x, \sigma_x^2)$ and $N(\mu_\epsilon, \sigma_\epsilon^2)$ respectively. Considering that the model is 2-staged, the Kalman algorithm for the two-stage donor search model, becomes:

$$\hat{x}_1 = (1 - K_0)\hat{x}_0 + K_0 s_0 \tag{101}$$

In addition to A, C, and G, let $\Sigma_0 = \sigma_x^2$ and $R = Var(s) = \sigma_x^2 + \sigma_\epsilon^2$. Substitution for K_0 and Σ_1 yields

$$K_0 = A\Sigma_0 G'(G\Sigma_0 G' + R)^{-1} = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\epsilon^2} \tag{102}$$

$$\begin{aligned}\Sigma_1 &= A\Sigma_0 A' + CC' - A\Sigma_0 G'(G\Sigma_0 G' + R)^{-1} G\Sigma_0 A = \sigma_x - \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\epsilon^2}\sigma_\epsilon^2 \\ &= (1 - \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\epsilon})\sigma_x^2 = \frac{\sigma_\epsilon^2}{\sigma_x^2 + \sigma_\epsilon^2}\sigma_x^2 = K_0\sigma_\epsilon^2 \end{aligned} \tag{103}$$

Combining (101) and (103) produces the mathematical expectation of x, given an observation s

$$\begin{aligned}\mathrm{E}[x|s] &= (1 - K_0)\hat{x}_0 + K_0 s_0 \\ &= \hat{x}_0 + K_0(s_0 - \hat{x}_0) \\ &= \mu_x + K_0(s_0 - \mu_x) \end{aligned} \tag{104}$$

Or, alternatively the filter can be represented in the form

$$
\begin{aligned}
\mathrm{E}[x|s] &= \hat{x}_t + K_0 a_t \\
&= \mathrm{E}[x] + K_0(s_0 - E[s_0])
\end{aligned}
\tag{105}
$$

with the updated belief about the variance defined by Σ_1. Consequently, the updated belief about the distribution of x, given s, is represented by $N(\mathrm{E}[x|s], \Sigma_1)$.

CHAPTER IV

AN EMPIRICAL ANALYSIS OF CHARITABLE GIVING BEHAVIOR IN AN ONLINE MARKETPLACE

4.1 Introduction

This chapter provides further analysis of charitable giving behavior, and roots the work of the previous two in an empirical foundation. It makes more tangible the notion of a charitable giving marketplace through the use of observational data provided from an online giving community for grassroots charitable causes. A relationship between the behavior of the donor, and that of the charitable organization is sought along two dimensions, in particular how organization behavior effects the amount that a donor gives, along with how organization behavior effects the likelihood of a donor making a subsequent future contribution. Behavior of the organization is defined with respect to transparency, and an attempt to explicitly parallel the donor search model of chapter 3 is made.

Beyond testing the assumptions and results of this search model, understanding the connection between the donor and a recipient organization continues to be important as it regards the questions of whether current humanitarian market funds are being used efficiently and effectively, and how might the market continue to grow and attract more donors. This chapter, much like the previous one, puts forth the contention that project or organization information, as it regards transparency, is at the root of understanding for both of these questions. Both of these perspectives are important as it relates to the effect that humanitarian giving can have on the lives of recipients.

The previous two chapters build on the foundational economic work of altruism and philanthropy, and put forth donor and organization behavioral models rooted in this work. Chapter 3, in particular, proposes a model rooted in two driving factors, *exposure* and *transparency*, of how donors respond to variations in organization behavior. At its core, the model and subsequent analysis is about understanding the role of information as a driver of the humanitarian marketplace.

A data set provided by GlobalGiving (GG), an online charitable giving market, is used along with several empirical methods to try to understand the effect of transparency related information on donor behavior. The GlobalGiving market structure, to a large extent, represents a self-contained version of the aforementioned donor search model, and consequently it provides a fairly reasonable test of the assumptions and results put forth previously. GlobalGiving requires that in addition to the initial due diligence process that all projects posted on its site post project updates, at a minimum, once every three months. These project updates, and the frequency at which they occur, are used as proxies for the transparency related variables in the donor search model. It is assumed that project updates are taken by donors, regardless of content, as signals of transparency and effectively lowers the monitoring cost associated with a particular project. The use of project updates as transparency proxies is a key innovation of this chapter, and offers a unique way in which to measure organization transparency levels. The extent to which these proxies effect giving behavior is explored.

The chapter begins with a brief review of relevant literature that guides not only use of the econometric methods, but also forms the foundation for behavioral assumptions. Section 4.3 provides an overview of GlobalGiving along with summary results of the provided dataset. Section 4.4 reviews the relevant donor search model, provides a framework for the empirical analysis, and proposes two hypotheses which drive the empirical analysis found within. The subsequent analysis focuses on the effect of transparency related information in two distinct ways. Part I focuses on information and its effect on the amount that a donor gives, and Part II focuses on information and its effect on a donor's likelihood of giving at all. Section 4.5 outlines econometric methods for how these questions will be probed, and using the fixed effects panel regression model and logistic regression models proposed in 4.5, section 4.6 presents the results of the subsequent analysis. In contrast to the assumptions the analysis does not show transparency related information, on average, to have a significant effect on the behavior of the population under analysis, with some noted exceptions. As a result section 4.7 considers validity issues associated with the analysis, and section 4.8 offers interpretations of the analysis along with directions for future work.

4.2 Background and Literature

First, it should be said that the research related to charitable giving, and understanding why and how people give is interdisciplinary by nature, and has been treated as such within the literature. To this extent Sargeant and Woodliffe [87] offer a comprehensive overview of the existing literature, and attempt to create a unified framework of factors in modeling and understanding donor behavior. In this respect, charity reputation has been shown to be a key component in effecting donor giving behavior. In fact, Meijer [61] uses data from the 'Giving in the Netherlands Project' to show exactly that. Meijer uses several proxies for charity reputation, and is able to confirm that the reputation of charity effects its ability to attract donors, but cannot confirm that the reputation is influential in effecting the level of the donation. Hsu et al. [47] conduct a similar study in which a survey is used to measure willingness to support Taiwanese charities, and also cite reputation as a factor in donor decision making. Venable et al. [99], Sargeant et al.[86] and Hibbert and Horne [44], and Radley and Kennedy [72] all propose donor frameworks for giving, and consider the role of charity branding and reputation in this process. While there is a relationship between an organization's reputation and an organization's level of transparency the two notions are not synonymous. To the extent that one can, this paper considers the role of transparency in establishing reputation, and by extension how it ultimately effects donation volume, and donation amount for a given organization. In particular, while there are several ways to proxy transparency this chapter considers a unique way to measure transparency as represented through project updates on the GlobalGiving website.

Beyond an extension of the notion of reputation in giving, this work builds off several disciplines, and offers to make a contribution in several areas as well. Because the framework for this empirical analysis essentially emanates from the confluence of consumer search models and donor behavioral models, the work can be placed along two dimensions. In particular it has a relationship with the literature that considers the empirical evaluation of search models, but also has a relationship with empirical work on charitable giving motivations and behavior. The preceding chapters offered up a review of some literature in both respects. A few relevant papers are highlighted here for each section, with potential contributions of the current analysis considered intermittently.

Looking outside of the realm of charitable giving behavior there have been several novel attempts at the empirical verification of search models, outside the that of traditional consumer search. In particular, building off of the Jovanovic [49] search model from which chapter 2's donor search model is derived Marinescu [58] attempts to describe the effect of shocks in the labor market on marriage duration. Garman et al. [36] use a model of donor search to describe participant behavior in a Person-to-Person lending market, and use data from Prosper.com to empirically verify their assumptions. Hitsch et al. [45] use a data set provided by an online dating service to empirically investigate search preferences in pursuing online mates. Their model makes several empirical contributions to the search literature and makes use of a similar discrete choice modeling methods used in this analysis. In this context the work in this chapter can be considered a contribution to the literature on empirical verification of search models, in particular through the use of a rather novel data set.

Within the framework of research into motives for charitable giving this chapter can also be considered distinct. There has been a plethora of research both theoretical and empirical on describing donor motivations for giving, and the effect of various types of information in altering donor behavior. List [55] provides an overview of how field experiments have come to be used with respect to the economics of charity. Works within this area of the literature include Croson and Shang [28] who investigate the impact of social information on giving through a field experiment with a public radio station. Alpizar et al. [2] considers whether context matters in how donors respond in willingness-to-pay scenarios when compared with actual contributions. Karlan and List [50] conducted a large-scale field experiment to ascertain the effects of price on charitable giving, and find that gift matching helps increase both response rate and the amount of the gift at the 1:1 level, but there is relatively little difference for increasing match rates. Rondeau and List [78] conduct a similar field experiment and conclude that challenge gifts positively influence contributions, but matching gifts do not. While the work of this chapter is not of the experimental variety it can be argued that it paves the way for such experiments by considering the role of transparency in giving, which has not been considered directly, to the author's knowledge, before now. There are tradeoffs in using observational data over explicitly defined experiments, but both are types of analysis are necessary in building toward a unified understanding of donor behavior, and how organizations can best respond.

This work is not the first to use empirical methods to evaluate charitable giving behavior, but does complement previous empirical studies. Kottasz [51] considers difference in the donor behavior of young affluent males and females in the UK. Woods [20] tests the notion of whether donors care about overhead costs through the analysis of giving behavior of federal employees in Chicago. Ribar and Wilhem [75] use panel data to empirical examine the effects of the *joy-of-giving* motive in driving donor contributions. Andreoni and Scholz [6] use econometric analysis to understand the effects of social reference spaces in influencing the charitable giving behavior of individuals. Lankford and Wyckoff [52] use Federal Tax File data, in conjunction with a Box-Cox standard tobit model to examine charitable giving behavior in the US population. Lastly, Sargeant et al. [85] provide an empirical based marketing model, using a survey of 1300 respondents, to understand how givers perceptions of organizations effect their giving behavior.

This analysis makes its primary contribution via its direct consideration of the effects of transparency on donor behavior through the use of observational dataset. The analysis further differentiates itself among other studies as it attempts to analyze a set of projects within a confined market, for which there were uniform barriers to entry. More explicitly, because projects are subjected to an upfront due diligence process they all meet some threshold level of credibility. Beyond that level is where the analysis takes place, and to some extent the model is as much a measure of the effect of institutions to provide legitimacy to groups of organizations, as it is a measure of individual organization behavior.

4.3 An Online Marketplace for Charitable Giving

4.3.1 GlobalGiving

Founded in February of 2002, GlobalGiving (www.GlobalGiving.com) is an online marketplace that brings donors together with grassroots charity projects from around the world. The stated mission of the organization is to, "Build an efficient, open, thriving marketplace that connects people who have community and world-changing ideas with people who can support them". The organization places a significant emphasis on providing a transparent and impactful experience for the donor via several mechanisms, as described below. In this vein, GlobalGiving is premised on the idea that people want to give, and will give to projects for which they can have a direct impact, can trust, and are verifiable in some respects. In addition to providing a reliable and impactful giving experience for the donor, GlobalGiving is also of the belief that healthy competition in the non-profit sector can encourage non-profit innovation and accountability.

Since 2002 GlobalGiving has been a conduit for over $19.2 million in donations from over 49,000 unique donors. GlobalGiving takes a nominal 10% fee from each donation for its work, and passes along the remaining contribtuions to the over 1,340 projects it has helped to provide with funding.

4.3.2 How it Works

To understand how the GlobalGiving site functions is to also understand why it works, in that the process by which donors and project leaders engage with the site is fundamental to understanding why GlobalGiving continues to grow, with increasing levels of donors and projects. How the process works is outlined below.[1]

- Project Leaders post their causes and details about what they need on GlobalGiving.com - giving donors an inside look at the project's unique needs and work being done.
- Donors browse the website, research causes by topic or location, and pick the one that matches their interests and passions.
- Donors make a tax-deductible donation and their gift is combined with other generous donors doing the same thing.
- GlobalGiving ensures that 85-90% of the donation is on-the-ground within 60 days and has an immediate impact.
- Donors get regular updates telling them what a difference their gift is making and the results that have been achieved.

[1] Adapted from http://www.globalgiving.com/howitworks.html (accessed May 2009)

Embedded within the story of how the process works is a good deal about why the process works. In particular the success of GlobalGiving can perhaps be understood along three dimensions; variety, credibility, and amenities.

4.3.2.1 Variety

With approximately 500 projects listed on the website GlobalGiving provides a large variety of options for potential donors, allowing them to capture donors of a wide range of preferences. More specifically projects from close to 100 countries are represented on the site, and can be classified within one of six global regions.[2] In addition to geographical variation the projects also vary by topic. GlobalGiving provides the donor with projects from 17 topic groupings that, much like the geographical variation, allows the site to retain donors over a wide range of giving interests.[3]

4.3.2.2 Credibility

While the project variety allows GlobalGiving to attract a wide range of donors, it is a high level of credibility that GlobalGiving uses as a differentiator from traditional charitable giving channels. GlobalGiving attempts to provide credibility both at the organization level, and at the project level. By providing credibility at the organization level GlobalGiving provides an implicit level of credibility to any project listed on the website, but beyond that level GlobalGiving encourages individual projects to maintain a high level of transparency and feedback to donors so that the projects can stand on their own as credible entities.

By providing a certain level of credibility and transparency it is assumed that donors will be more comfortable giving to projects listed on the site, and should in fact be willing to give more, and give more often. As outlined in "How it Works"

[2] Africa, Asia and Oceania, Europe and Russia, Middle East, North America, and South/Central America and the Caribbean

[3] Project topics include: Animals, Children, Climate Change (GG Green), Democracy and Governance, Disaster Recovery, Economic Development, Education, Environment, HIV-AIDS, Health, Human Rights, Malaria, Microfinance, Peace and Security, Sport, Technology, Women and Girls

GlobalGiving fosters credibility and transparency through several mechanisms.

One of the primary mechanisms in providing credibility to projects listed on the site is the *due diligence* process that GlobalGiving adheres to when vetting projects to appear on the website. The due diligence process is characterized, in addition to other factors, by projects meeting the following criteria:[4]

- Their work has significant social impact.
- They have a track record for delivering on promises.
- They are not listed in any terrorist databases.
- Their projects are eligible for international philanthropic donations so donors in the US receive full tax benefits.

This process provides the donor with upfront knowledge that each of the listed projects meets these qualifications at a bare minimum.

In addition to the due diligence process GlobalGiving also encourages projects to provide frequent updates on progress, allowing donors to stay engaged with the project and monitor the impact of their donation from afar. GlobalGiving rewards projects with frequent and informative updates through higher rankings, as discussed below. Beyond providing another means by which projects can distinguish themselves from others, project updates help to provide an additional layer of credibility. While the due diligence process helps to establish GlobalGiving as a credible organization, the project updates allow individual projects to further assert themselves as reliable investments. Figure (25) highlights the distribution of project updates amongst the projects found within the provided dataset. While the amount of updates for a given project varies over time, Figure (25) uses the total number of updates for a given project during its last occurrence within the set.

[4] Adapted from http://www.globalgiving.com/aboutus/dd.html (accessed May 2009)

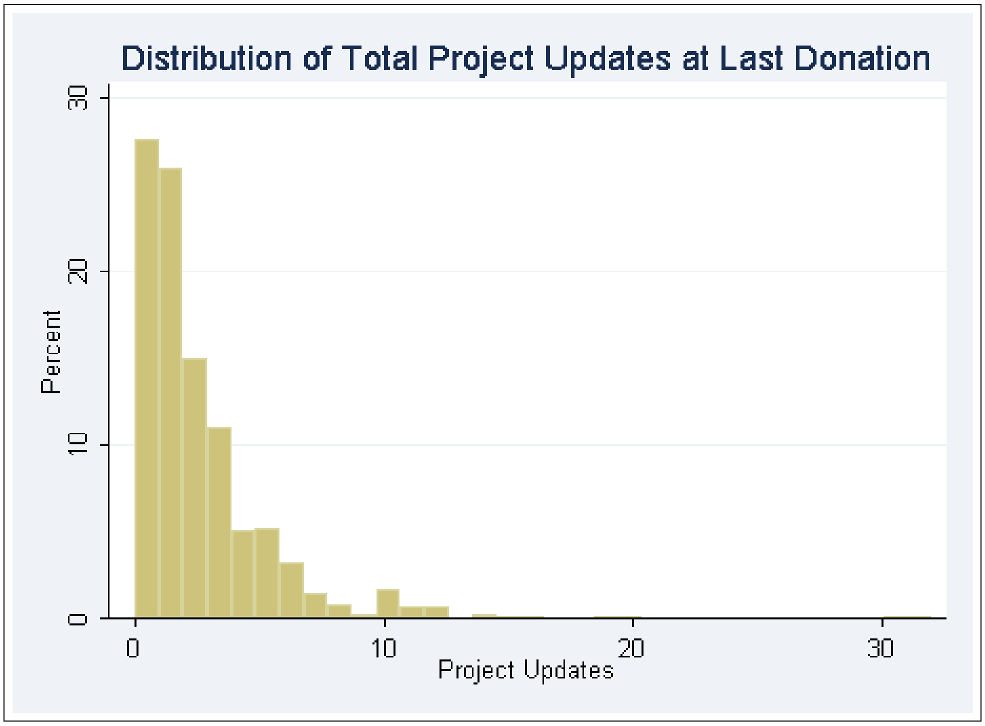


Figure 25: Distribution of project updates for the last project occurrence within the data set.

A third mechanism by which GlobalGiving helps to reassure the donor of the quality of the site's projects is "GlobalGiving Guaranteed."[5] The is GlobalGiving's commitment to offering a moneyback guarantee, in the form of a voucher, for any donor who is not satisfied with their giving experience. Much like in the for-profit sector, this guarantee helps to underscore a level of confidence in the quality of the product that GlobalGiving is offering, which in this case are the charitable projects([67]).

As a collective these mechanisms help to provide both GlobalGiving and subsidiary projects with a strong brand as it concerns credible and quality projects. GlobalGiving's focus on these issues as an organization is of benefit to the empirical analysis in this paper, as the primary focus is on characterizing the importance of these factors as it relates to the donor giving experience, and the propensity for giving.

[5]http://www.globalgiving.com/guaranteed/ (accessed May 2009)

4.3.2.3 Amenities

In addition to variety and credibility the GlobalGiving market has several other features which help to enhance its usefulness to donors, and distinguish it from other online giving communities. These features are classified under amenities in this paper, as they represent features that are not critical to the market success, but help enhance the viability of the marketplace as a first option of charitable givers.

Crucial to the success of the market in attracting and retaining potential donors is the time it takes a potential donor to find a project to which he wants to make a donation. In this respect, how efficiently a donor can search the site, and on what dimensions, is an important market characteristic. To address this issue GlobalGiving offers the potential donor several search options. In addition to the donation wizard, which makes project suggestions after the donor responds to a few questions, the site allows the donor to search for projects along the following dimensions:

- Project Theme
- Country/Region
- Closest to Goal
- Newest Projects
- Recently Updated

Furthermore, within each of these search categories projects are given a ranking as a function of several factors, such as the projects most recent update, the amount of funding received relative to other projects, the amount of donors the project has attracted, and how close it is to its fundraising goal. This ranking allows projects to be presented in the order of those that GlobalGiving believes to be the "best" in the sense that they have received a higher GlobalGiving ranking.

In addition to facilitated search and project ranking, other market amenities include the option for donors to setup wedding registries, sponsor fundraisers, or purchase gift cards.

Understanding how GlobalGiving works is essential to understanding the meaning of the analysis contained herein, and in particular it helps in contextualizing the data set used in this analysis.

4.3.3 Data and Donor Characteristics

For this empirical study of donor giving behavior in response to project related information, GlobalGiving provided an anonymized data set of donations spanning an 11 month period from February 1, 2008 to December 31, 2008.[6]. The remainder of this section will describe the contents of the data set along with the presentation of some preliminary summary statistics.

The provided GlobalGiving dataset contains close to 20,000 observations, where each observation is a donor gift to a specific project. Each observation contains information about the donor and information about the project that received the gift. Some summary statistics of project and donor characteristics are given below.

Distribution of gifts by date Figure (26) shows the distribution of the donations provided via GlobalGiving by the day the gift was made. As can be readily seen there are two periods in which the volume of giving seems to dramatically deviate from the average level. Specifically, the months of May and December appear to be aberrations, and in fact they account for 28% and 23% of the donations within the provided set. The increase in giving associated with December can be perhaps be explained by an end of the year giving surge for individuals wanting to receive charitable tax deductions on their current year income tax returns. In this sense, December would always exhibit deviant behavior with respect to the rest of the year's average level of giving. May, however, experienced an aberration in giving because of two high profile natural disasters that occurred in succession of one another. On May 2nd, 2008 Cyclone Nargis hit Myanmar causing over 146,000 fatalities and thousands

[6]The month of January was excluded because of a special promotion that was running on the site at that time, which highly skewed the amount and type of donations made from normal activity

of injuries. Shortly thereafter on May 12th an earthquake hit Sichuan Province of China resulting in over 68,000 fatalities. The occurrence of both of these significant disasters within days of each other caused May to be the highest giving month of 2008 on the GlobalGiving website. The average number of donations per day over the entire data set is 59.07 donations per day. May and December each averaged 169.9 and 149 donations per day respectively.

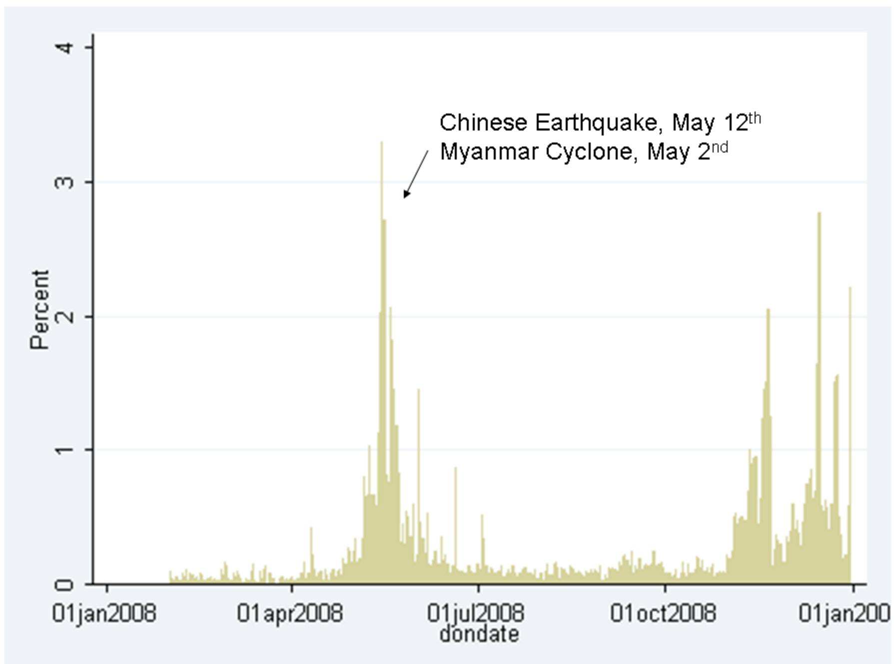


Figure 26: Distribution of Donations via GlobalGiving by Date

Donations by project theme There are 706 projects in the set that vary by theme as described above. 14 of the 17 project themes are represented in the provided set with the total amount of donations accrued to each theme over the data set as outlined in Figure (27). Children, disaster, education, and health themed projects accounted for 15%, 26%, 13%, and 21% of the unique gifts within the data set. Donations from the month of May inevitably accounted for the large volume of disaster themed project donations, with 75% of these donations occuring within the month.

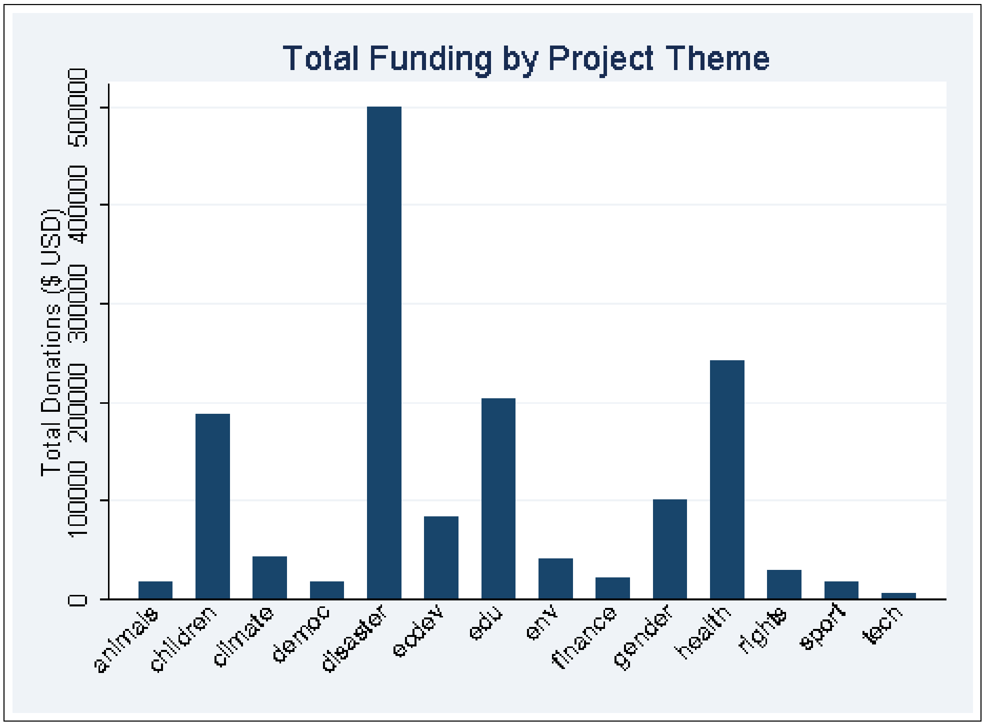


Figure 27: Total Funding by Project Theme

Donations by country As one would expect given the aforementioned distributions, China and Myanmar received the 1st and 3rd largest amount of total donations by country, accruing 28% and 6.2% of approximately $708,000. India was second largest with 7.4% of the total donations made over the data set. Figure (28) outlines this figure for the top 6 countries as ranked by the percentage of total donations captured over the data set.

4.3.3.1 Derived Variables and Truncated Data

Because of the nature of the GlobalGiving data set, the discussion, to ensue later, of what regressors to include in associated empirical models must implicitly include a discussion of which observations to include in the final evaluation set. In particular, because of the nature of the set certain variables can only be derived for projects that started after the data set begins, February 1, 2008. Consequently, it becomes an important consideration in determining which variables to include in the regression

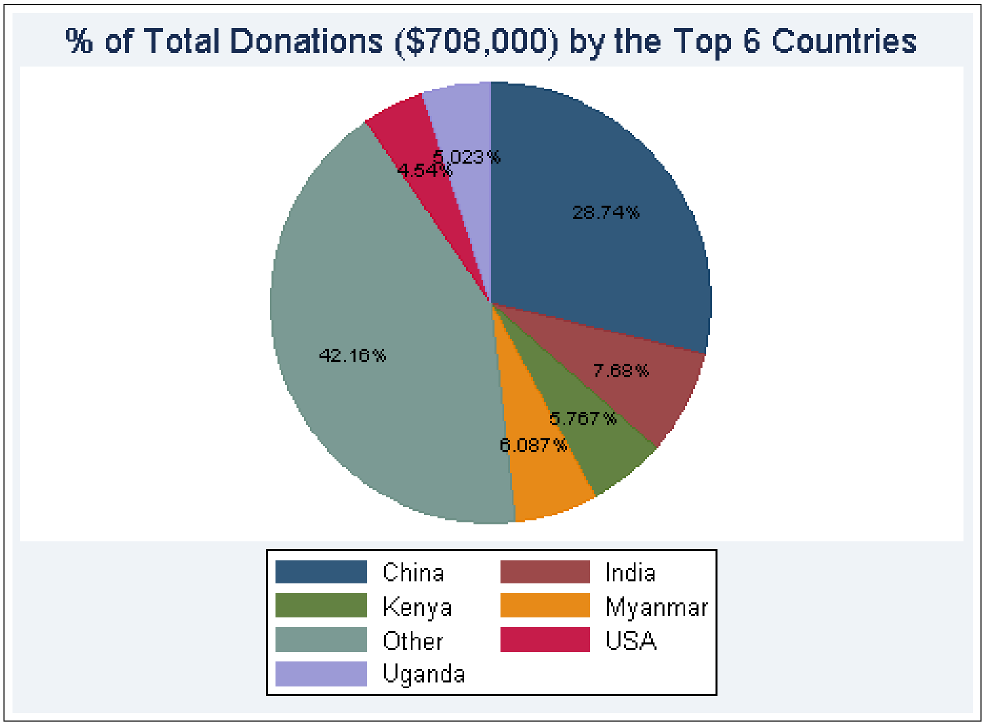


Figure 28: Percentage of Funding by Country

analysis. Because not all projects in the data set begin after February 1st, it would become necessary to exclude projects initiated earlier from the analysis if one of the associated regressors were to be included. In real terms this would require removing about 36% of the observations from the data set, leaving just over 12,500 for evaluation. An even further paring of the data occurs, as outlined in the next section, when one wishes to consider the question of wehther or not a donor gives again. In this instance the set is effectively reducded to around 7,000 observations.[7]

[7]It should also be noted that analysis is confined to those donations between $10 and $100 as the donor search model is primarily concerned with those who gave in small amounts. Additionally, this range accounts for approximately 90% of the donations found in the set.

4.3.3.2 Coding Multiple Donations

An important feature of the data set with respect to the empirical analysis to follow is the ability to ascertain whether, after an initial donation, a donor makes a subsequent contribution.[8] Furthermore, it can be determined whether that subsequent contribution was made to the same project as the initial contribution, or whether it was made to a different project. In this sense, it becomes necessary to code each observation with whether or not there is a subsequent donation, and if so, of what type.

Given a donor and his initial donation to a project either one of three things can occur subsequent to this donation:[9]

1. A donor can donate to this project again at some point in the future.

2. They can donate again in the future to a different project.

3. They can choose not to donate again.

Given these three possible outcomes there are several ways of coding the data to represent the scenarios, each with some advantages and drawbacks. A simple and straightforward way to consider coding these scenarios is something along the lines of the following:

Each observation in the data set is coded with 0, 1, or 2 denoting one of the three scenarios. If an observation is coded with a 0 then the donor made a subsequent donation, but not to the project listed in the current observation. An observation

[8] Each donation by a donor is treated as an initial donation. As such it is possible to ascertain for every observation within the set whether or not their was a subsequent donation made by that donor.

[9] In this analysis if a donor makes multiple initial donations to a suite of projects on the same day, then each of these donations is treated as a unique instance and analyzed as such. In this way, if donor 3 contributes to projects A and B on the 1st of February, and then contributes only to project A later in the data set then the first observation of the contribution to A is coded with a 1, and the observation in which the donor contributes to project B is coded with 0.

coded with 1 denotes a donor who made a subsequent contribution to the same project. An observation coded with 2 denotes a donor who does not appear in the data set again after the current observation.

While seemingly straightforward, this initial coding is complicated by censoring issues that arise from the data. Because the data set ends on December 31, 2008 it is entirely possible that a donor who gives on December 15, 2008 does give again, but because it is not until January it is coded in the data set as 2. In fact, given that a rather large number of donations occur within the last month of the year, it is quite possible that this censoring problem skews the coding of the data in a significant way. There are, in fact, a few ways to better code the data such that this problem can be mitigated to some extent.

One way to do this is to assume that the set of observations ends at some time before December 31, 2008, and only code observations to that point. Whereas now there is no post-December 31st information available for any of the observations, one can generate a data set for which there is post-termination information. For instance, if the set is cut such that only observations before December 1st are considered then donor's who make a contribution toward the end of the that set have at least a 31 day window in which one is able to see whether or not that donor contributes again in that time period. While this method does help eliminate some of the bias, it also requires that 23% of the observations are lost. However, even beyond the issue of lost observations the question of what is the appropiate cutoff point persists. Leaving 31 days to observe end of period donors might not be benenficial at all if the the average time for a repeat donor is longer than 31 days. In fact, if one does an inital coding in the manner proposed above the average time, in days, for a donor who does give again to make a subsequent contribution is 34.15 days. Additionally, the median number of days for donors who do give again is 20, while 75% of those who give again do so in 33 days or less. These numbers suggest that 31 days might be a feasiable cutoff point, in that it could provide a workable time window in which to observe whether or not a donor gives again or not. In general, with data of this sort this censoring problem will always be an issue when trying to determine behavior over an extended period of time for individuals. Regardless of the time period which is avaiable within the data set, it can always be said to be the case that there are donors who are going to give again but have not done so yet.

The previous paragraph hints at a problem of another potential solution, which is to collect data for individual donors beyond the December 31st cutoff, until the present. In this way, for each donor in the original data set whether or not they enter the set after the cutoff point is ascertained. While this is ideal in some respects, such data is not available, and if it were it still fails to avoid the censoring problem.

Another alternative solution to help mitigate the censoring problem is to standardize the interval over which all observations are considered. Both of the prior solutions offer alternatives which are meant to deal with the issues regarding observations found near the end of the data set. However, there is still an issue in that because of the serial nature in which observations occur, those at the beginning of the data set will always have a longer period over which to be observed than those at the end of the set. A potential antidote to this is to consider all observations over a standardized period, such that if a donor does not give again over the course of a pre-defined interval, then it should be considered not to have given again at all. In this sense, if one were to define the interval at 100 days, then the coding could look something like the following:

An observation is coded with a 0 if the donor makes a subsequent donation within 100 days of his current donation, but not to the project listed in the current observation. An observation is coded with a 1 if a donor makes a subsequent contribution to the same project within 100 days of the current donations. An observation is coded with a 2 when a donor does not appear in the data set again after the current observation, or when the donor makes a subsequent donation after the 100 day interval.

Considering the donations within the standardized framework helps to provide consistency over the analysis and eliminate some of the problems related to bias. While a seeming improvement over the previous coding proposals, there are still some issues that arise when one considers which variables are available as regressors in the model, and how many observations are lost via selection of the evaluation interval. Issues related to potential regressors are discussed later on within the context of the discussion as to which variables should be included in the model. Much like the previous solution of advancing the cutoff point of the data set, analysis by interval runs into the same problem of lost observations, and what is the appropriate interval over which to evaluate.

The problem of lost observations occurs because observations who enter the data set in a period in which they do not have enough time to be evaluated over the selected interval cannot be included in the analysis. Thus, if 100 days is the selected interval then all observations within the last 100 days of the year are dropped, which in this context amounts to 47% of the observations. This is a fairly significant number of observations, and so consideration must be given to the question of what the appropiate interval should be in the context of both the number of observations lost, and the number of days in which it is feasiable to expect a repeat donor.

An initial coding of the observations occurs in which a variable, *giveagain*, is coded to take on the values is defined by the initial coding without intervals. Approximately 9% of the donations are coded such that they indicate that a subsequent donation followed (i.e. $giveagain = 0$ or 1). This provides a foundational point to consider how the dataset changes as the decisions about potential intervals are considered. As mentioned above, of those who give again, 50% of the donations come within 20 days, and 75% come within 22 days. Additionally, 99% of the repeat donations occur within 102 days of the intial donation. Looking at the effect of several intervals on the distribution of the *giveagain* coding within the data set, we initially proceed with a 100 day interval over which to evaluate donor behavior.[10]

Lastly, it is worth considering that none of these solutions are not without criticism, but are perhaps among a set of best alternatives given the empirical constraints of the data set. One question for consideration is the question of what it means for a donor to give again after 100 days, or after a defined interval period in general. As of now, those donors who give again after 100 days are considered to not have given at all, and are coded as a 2, which may be appropriate in some sense, particularly if there is not a significant difference in the characteristics of the two groups. However, consideration that those who give again after 100 days might be significantly distinct from those who don't give again is a worthwhile exercise. For now however, because of the relatively small number of observations which fall into the category of providing repeat gifts after 100 days, the data will be coded in the aforementioned 0,1, 2 framework. Further discussion of this derived variable will arise in the context of its use as a regressor.

4.4 A Modeling Framework for Analyzing Donor Behavior

Chapter 2 presents a two-stage donor search model from which the empirical analysis is in part derived. The model considers charitable projects to be public goods, and is based on the idea that individuals with heterogeneous preferences over these projects want to contribute monetary gifts toward them and are motivated by both private and public aspects of the gift and good. The model is a selection model which considers a market with donors who want to buy public goods, and charities which provide them. This two stage model consists of an introductory stage in which donors

[10] 100 days is considered to be exclusive of the day the initial gift was made, so the interval of observation is 100 days after the intial day

are introduced to a particular project or organization via a weighted introduction mechanism. The donors, once introduced, must make a decision about whether to contribute toward the project or take a pass and continue looking for a worthy project (i.e. accept or defer). The donor's first stage decision of whether to pass or not is driven by two factors; the expected benefit from making the contribution, of which there are both public and private components, and his view of the cost to monitor the organization (or transparency cost). If the expected benefits outweighs the perceived costs by enough then the donor will choose to make a first stage contribution. If the donor contributes during the first stage then a second stage decision presents itself. This decision differs from the first stage decision because the donor now has more information about the quality of the project or organization, and his satisfaction with the internalized benefits. The second stage decision is presumed to be one in which the donor decides either to return to the pool of potential projects, or matches with the current project.[11] This model is analyzed with an eye toward understanding the effects of monitoring costs (transparency) and exposure in driving donor behavior and market dynamics. Several implications arise from the model:

1. A reduction in monitoring costs within the market, by individual organizations, expands the size of the overall market.

2. Unilateral transparency increases, by individual organizations, have effects that are relative to the transparency level of the market as a whole. If transparency across the market is high, a 10% increase in transparency by an orgnaization A will yeild less gains from donors when compared to a 10% increase in a low transparency market.

3. An organization's exposure level is a primary driver in attracting donor's, and

[11]In this context match is used to denote a donor and organization pairing which is stable, in the sense that the donor does not desire to break the pairing.

to some extent can overcome any decrease in donations due to transparency related issues, at the margins.

More pointedly, there are two aspects of this work which are of interest $vis - \grave{a} - vis$ empirical analysis of the GlobalGiving data set. This model rests on several assumptions about what both donors and organizations care about, and through these assumptions and analysis of the model several testable hypotheses emerge with regard to donor and organization interaction within the charitable giving market. Through the lens of the data set this section defines two specific hypotheses which guide the subsequent analysis.

The GlobalGiving provided data set is absent some key variables which would allow for a more through testing of assumptions and results implied by the donor search model.[12] However, the data set does offer the opportunity to test the effects of various types of information on donor behavior and organization fundraising, with some tests emanating directly from the aforementioned theoretical models, and others which are related but not explicitly modeled from a theoretical standpoint. In particular the donor search model does not tackle the question of the amount of the gift, but only the disbursement of the gift as altered through organization exposure and transparency levels.

While this work advances the theoretical basis of discrete choice selection as it concerns organizations in a charitable marketplace, it does so by advancing the notion that certain types of information matters in giving. From this perspective, the GlobalGiving data set allows one to test notions of behavior alteration in the face of various scenarios. The set is particularly suited to a model construction which might allow one to infer the role of information on the level of giving, which was deferred in the theoretical treatment.

[12](i.e. the opportunity pipeline, page layout information, etc.)

What follows is a two part treatment of the analysis of information effects on giving. Part I focuses on its effect on the amount of the donor's gift, and part II will focus on the donor's allocation decision.

4.4.1 Part I: Information and its Effect on the Level of Gifts

This treatment results from a confluence of the information available within the GlobalGiving dataset and the theoretical development of the role of information in donor giving. The donor search model develops formal claims about the effect of information on donor giving behavior. In particular the hypothesis is formulated such that increases in exposure levels for a given organization, along with investment in the reduction of donor monitoring costs (a monitoring cost reduction can equivalently be thought of as an increase in transparency) will lead to a higher likelihood of selection by a given donor, with all other attributes being controlled for. H1 extends that notion to the amount of the gift, and hypothesizes that reductions in monitoring costs will lead to higher donation levels for a given organization.

H1: *Controlling for all other attributes of both the donor and the organization, an increase in the transparency level of an organization will lead to an increase in the amount donated by an individual donor.*

More formal meaning will be brought to some of the language used in H1, particularly in regards to how one might measure the transparency level of a project or organization . H1 says that for a donor who is already pre-disposed to give to an organization A, he will increase has donation level in relation to an increase in the transparency level associated with that organization. To test this hypothesis a panel regression with fixed effects is used, with an ordered logit model considered as an extension.

4.4.2 Part II: Information and its Effect on the Allocation of Gifts

While section 4.4.1 can be considered an extended test of the donor search model results, this section shifts the focus to testing the specific results derived from the donor search model as it regards likelihood of selection from the organization standpoint. The main result from the model was the effect of exposure and transparency on the likelihood of organization selection, as distinct from the gift amount hypothesis put forth in the previous section. H2 defines the hypothesis under consideration here.

H2: *Controlling for all other attributes of both the donor and the organization, an increase in the transparency level of an organization will lead to an increase in the likelihood that the organization is selected to receive a donor's gift.*

H2 deals with the the probability of an organization being selected relative to all other similar organizations, while H1 dealt with how much a selected organization would receive, given that a donor has already settled on this organization. H1 and H2 both make claims about the usefulness of certain information in aiding donor decision making, but take a different perspective on its use. Neither are mutually exclusive, and in fact it is not beyond reason that for a given donor, information will enter his decision process in both respects. H2 lends itself to verification via a conditional logit model.

4.4.2.1 Dataset limitations with respect to the H2 Hypothesis

Before preceding to the model specification it is important to consider what the dataset allows one to test via the H2 hypothesis and the associated search model. As alluded to previously, there are pieces of information missing from the dataset which preclude a full testing of the donor search model. Consider a s simplified version of the previously described search model in Figure (29) that excludes the introduction stage. It becomes apparent that the contents of the GlobalGiving data set do not permit analysis of information's effect on a donor's first stage decision (i.e. the donor's defer

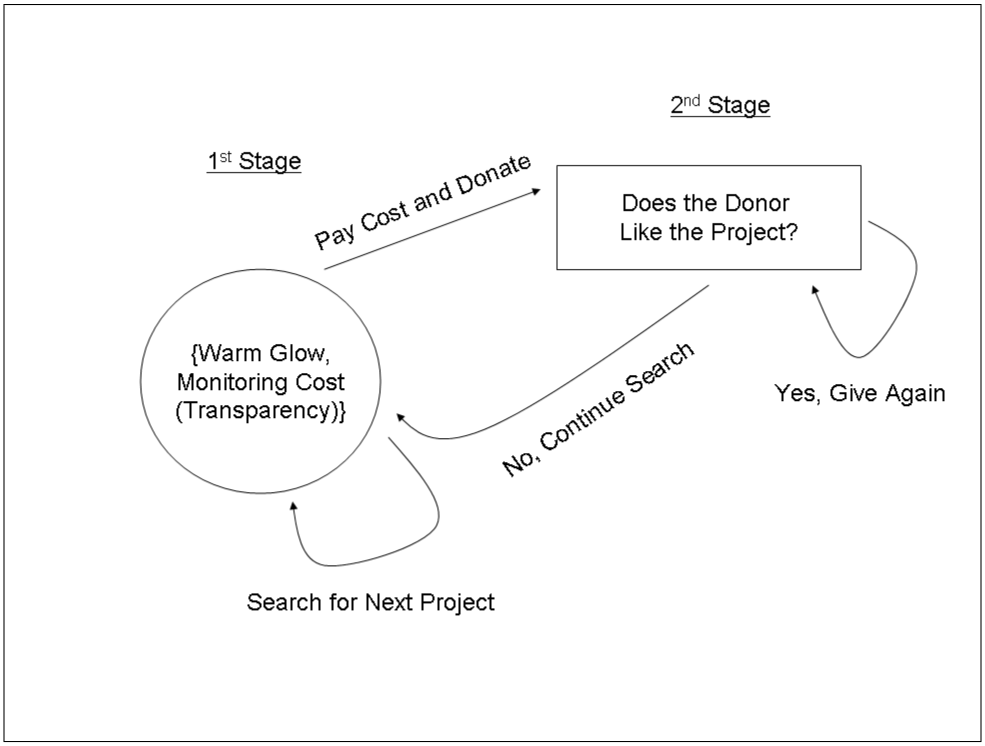


Figure 29: A Simplified Two-Stage Donor Search Model

or accept decision for a given project). Said another way, the GlobalGiving dataset begins at the point where the donor has already agreed to "Pay Cost and Donate" for a given project. Consequently, given the construction of the dataset, one does not have access to information about the number and type of alternatives that a donor considered before making the observed project contribution, making it difficult to make conjectures about the factors that influence this initial selection. However, what one can hope to establish is, given stage 1, a set of factors that can predict match sustainment at stage 2.[13] As section 4.3.3.2 outlines, what can be drawn from the dataset in support of this is information about how many contributions specific donors made, as identified via a unique identifier, to various projects, and whether or not donors made those contributions to the same projects, or different

[13]Stage 2 analysis suffers from some of the same missing data problems as the stage 1 analysis does, but because the question being asked is fundamentally different its effect is limited.

projects, in successive periods. The availability of this information, coupled with project attributes and donor characteristics, allows one to construct an econometric model that can make claims as to the likelihood of a given donor to give again to the same project, give again to a different project, or not give again at all.

4.5 Econometric Specification

4.5.1 Panel Regression Model with Fixed Effects

Section 4.6.1 considers more thoroughly how the following model is justified, for now the model is presented generally, and then specified for the specific context outlined above. If Y_{ijt} is the amount donated by donor i to project j in period t, then the population regression function (106) defines the relationship between project attributes, donor characteristics, and Y.

$$Y_{ijt} = \beta_0 + \mathbf{x'_{jt}}\beta_\mathbf{1} + \mathbf{x'_{it}}\beta_\mathbf{2} + \alpha_\mathbf{j} + \epsilon_\mathbf{ijt} \tag{106}$$

$\mathbf{x'_{jt}}$ and $\mathbf{x'_{it}}$ are vectors of observable project attributes and donor characteristics, respectively. Additionally, α_j represents unobservable project specific fixed effects, and ϵ_{ijt} are all remaining uncorrelated unobservables. Using project update related attributes as proxies for transparency, equation (106) is extended such that it has relevance to the considered data set and the available attributes and characteristics one can define the following:

$$\begin{aligned} Y_{ijt} = \beta_0 &+ \beta_1 numprojupdts_{jt} + \beta_2 daysfrmlastupdt_{jt} + \beta_3 numprevdonors_{jt} \\ &+ \beta_4 amtofprojfunded + \beta_5 projage + \beta_6 subscribe_{it} + \beta_7 guestcheckout_{it} \\ &+ \beta_8 may_{it} + \alpha_j + \lambda_t + \epsilon_{ijt} \end{aligned} \tag{107}$$

The number of project updates posted at the time the donation was made (*numprojupdts*) along with the days since the last project update (*daysfrmlastupdt*) are used as proxies for transparency, and are the primary regressors of interest. However, in addition to the variables of interest it is also necessary to control for other relevant factors which might contribute toward the decision of how much to donate to a particular project. The choice of which factors to control for is in part informed by some of the aforementioned research in section 4.2 on how donors make giving decisions. In particular, the number of previous donors to a project at the time of donation (*numprevdonors*) along with the amount of funding the project has received to date as a percentage of its funding goal (*amtofprojfunded*) are considered to be influential in shaping a donor's donation level decision. To control for these variables with respect to how long the project has been available for funding the project's age (*projage*), in days, is also included.

In addition to project attributes several observable donor characteristics are also considered. While most donor characteristics remain unobservable, the existence of characteristics such as whether or not the donor subscribes to the GlobalGiving newsletter (*subscribe*) or whether or not their donation was made via a guest account (*guestcheckout*) allows one to segment the donor population at a very coarse level. In this way, one can ascertain whether one type of donor is more pre-disposed to higher giving, or repeat giving, than another.

4.5.1.1 Fixed Effects

Project characteristics vary across several dimensions, most notably the theme of the project and the country in which it takes place. It is assumed that individual donors, exclusive of the aforementioned regressors, have preferences over the type of projects they like to fund. For instance, an investment banker with an altruistic streak may be more inclined to donate to mircrofinance related projects as opposed to education related projects. Consequently, this donor may be willing to settle for a lower level of transparency in exchange for a stronger project match along the lines of thematic preference. While the project theme is observable, one can easily imagine other project attributes that may bias a donor's decision process that are not observable within the set. One such unobservable might be the public opinion as it concerns the perceived *value* of the project. A project, by its nature, may be considered to be of high value and so its higher donation levels are not a result of more or less relative transparency, but simply a function of its perceived value.

Alternatively, from the project perspective, because it is considered a high value project, it may be of the belief that greater transparency will cause increased donation amounts. This would then cause a project to provide more updates than it would relative to other projects, as driven by its value attribute. It soon becomes clear that an unobservable project related value attribute can be correlated with both the dependent variable, along with an independent regressor. To control for these project specific unobservables a fixed effects regression model is used, whereby α_j is added to the model for each project j, and are considered to be entity fixed effects which control for the unobservable variables related to each project.

4.5.1.2 Time Effects

While the model has been specified as one in which fixed effects are accounted for, there is also some concern that unobservable time effects may play a role in shaping behavior as it regards a donor's gift amount. As discussed in section 4.3.3 there were two months in particular in which the volume of the donations were high relative to other months, May and December. These abnormalities suggests that there may be some time effects which are necessary to control for. Consequently, an attempt is made to control for time effects on the level of giving by adding dummy variables (λ_t) for each of the T-1 (T = 11) periods for which the data set spans.

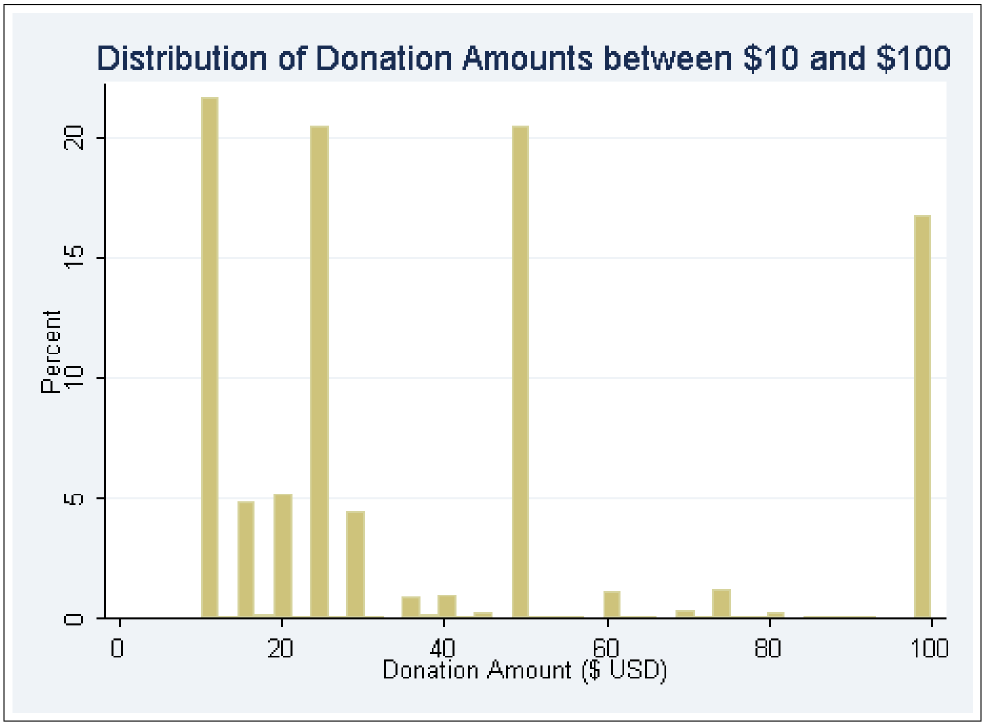


Figure 30: Distribution of the Donation Amount

4.5.2 Ordered Logit Model

As mentioned previously, for the level of giving analysis, the data has been truncated such that only donations between $10 and $100 appear in the dataset, as interest is confined to the behavior of donors who give in relatively small amounts. Figure (30) shows how the donations are distributed based on the amount given. Easily seen from the figure is that donations appear to occur primarily at 4 distinct levels $10, $25, $50, and $100. This grouping of data is largely a by-product of the way donation options are presented on the GlobalGiving website. While individual donors are free to give at any level they choose, each project comes with a menu of options with suggested donation amounts, and what each amount can buy with respect to that project. Not surprisingly these values usually begin at the $10 and $25 levels, with one step above these levels are the $50 and $100 levels. As a consequence donor level decisions are somewhat bias toward these groups. Consequently, it is worth considering how project information effects the probability of a donor selecting into a specific donation grouping. Because the groupings are ordered and represent a discrete choice decision an ordered logit model is used for analysis.

The dependent variable (*dongroup*) is coded to represent four donation levels at which a donor can give. Using the 25th, 50th, and 75th percentiles as cutoff points *dongroup* is coded as follows:

$$dongroup = \begin{cases} 1 & \text{if Amount Donated} \leq \$15 \\ 2 & \text{if Amount Donated} > \$15 \text{ and} \leq \$25 \\ 3 & \text{if Amount Donated} > \$25 \text{ and} \leq \$50 \\ 4 & \text{if Amount Donated} > \$50 \text{ and} \leq \$100 \end{cases}$$

Given an ordered choice set as the dependent variable an ordered logit model is derived from a generic latent regression model ([39]), whereby

$$y^* = \mathbf{x}'\beta + \epsilon \tag{108}$$

y^* is unobserved, but what is observed is the censored group value as derived through (109).

$$\begin{aligned} y &= 0 \text{ if } y^* \leq 0, \\ &= 1 \text{ if } 0 < y^* \leq \mu_1, \\ &= 2 \text{ if } \mu_1 < y^* \leq \mu_2, \\ &\vdots \\ &= J \text{ if } \mu_{J-1} \leq y^*. \end{aligned} \tag{109}$$

The μ values (cutoff points), assuming the error terms (ϵ) are i.i.d. with type I extreme value distribution, $F(\epsilon) = exp(-e^{\epsilon})$ are then estimated via the following,

$$
\begin{aligned}
Prob(y = 1|\mathbf{x}) &= F(\mu_1 - \mathbf{x}'\beta) - \mathbf{F}(-\mathbf{x}'\beta), \\
Prob(y = 2|\mathbf{x}) &= F(\mu_2 - \mathbf{x}'\beta) - \mathbf{F}(\boldsymbol{\mu_1} - \mathbf{x}'\beta), \\
&\vdots \\
Prob(y = J|\mathbf{x}) &= 1 - F(\mu_{J-1} - \mathbf{x}'\beta),
\end{aligned} \tag{110}
$$

where $0 < \mu_1 < \mu_2 < \cdots < \mu_{J-1}$.

Defining (110) for $dongroup_{ijt}$ yields the following,

$$
\begin{aligned}
Prob(dongroup_{ijt} = 1|\mathbf{x}) &= F(\mu_1 - \mathbf{x}'\beta) - \mathbf{F}(-\mathbf{x}'\beta), \\
Prob(dongroup_{ijt} = 2|\mathbf{x}) &= F(\mu_2 - \mathbf{x}'\beta) - \mathbf{F}(\boldsymbol{\mu_1} - \mathbf{x}'\beta), \\
Prob(dongroup_{ijt} = 3|\mathbf{x}) &= F(\mu_3 - \mathbf{x}'\beta) - \mathbf{F}(\boldsymbol{\mu_2} - \mathbf{x}'\beta), \\
Prob(dongroup_{ijt} = 4|\mathbf{x}) &= 1 - F(\mu_3 - \mathbf{x}'\beta),
\end{aligned} \tag{111}
$$

where the regression vector $\mathbf{x}$ is defined as in equation (107).[14]

4.5.3 Multinomial Logit Model

Sections 4.5.1 and 4.5.2 developed models to test transparency effects on the level of giving. Here a multinomial logit model is developed along with associated binomial conditional logit models to test the H2 hypothesis with respect to the donor search model. Similar in concept to an ordered logit model, the multinomial logit model allows one to estimate the odds of a donor selecting into one of several unordered groups, dependent on project attributes and donor characteristics. While potentially beneficial it is not clear that the multinomial logit model offers greater insight into the effects of transparency on matching than any of the conditional logit structures

[14] Discuss incidental parameter problem, and the need to drop projects with frequencies less than 30.

defined below. Each of the logit models is derived with respect to the dependent *giveagain* variable. The ability to structure this variable such that it represents either a binomial or multinomial choice set rests at the center of the subsequently outlined models. Assuming the error terms (ϵ_{ij}) are i.i.d. with type I extreme value distribution, a generic logit model over a size J choice set can be represented as

$$\text{Prob}\{Y_i = j|\mathbf{x_i}\} = \frac{\mathbf{e}^{\beta_\mathbf{j}'\mathbf{x_i}}}{\mathbf{1} + \sum_{\mathbf{k=1}}^{\mathbf{J}} \mathbf{e}^{\beta_\mathbf{k}'\mathbf{x_i}}} \tag{112}$$

Given the coding outlined in section 4.3.3.2 logit modeling is used to consider the likelihood of selection among the choice set

$$\begin{aligned} k \in \{0 &= \text{give again to the same project,} \\ 1 &= \text{give again to a different project,} \\ 2 &= \text{don't give again}\} \end{aligned} \tag{113}$$

The set of regressors defined here is much the same as in the previous two sections, however because of the temporal nature of the *giveagain* variable, between period variables are also included within the model. Recalling that *giveagain* is defined over a 100 day interval, one is able to record project attributes over this interval, for each project. In particular one can derive the number of donors that contributed to the project during the interval (*totaldonors100*), the number of project updates posted (*numprojupdts100*), and the amount of money raised as a percentage of the desired funding goal (*amtprojfunded100*) during the interval. These regressors are added to the model, as they would presumably have an effect on a donor's likelihood of contributing toward the same project in the future.[15] Additionally, how many

[15] It should be noted that if a donor donates again to either his initial project or a different project then these marginal variables may not be exactly aligned with the interval between the initial gift and the subsequent gift. In fact, this will be the case anytime the time between gifts is not 100 days. In this respect a variable such as *numprojupdts100* may include updates that were not present

donations a particular donor has made (*numdonofdonor*), inclusive of the current donation, is also included as a regressor. For $\mathbf{x}$ containing the previously described regressors, a logit model over the donor choice set (113) can be described via (114).

$$\text{Prob}\{giveagain_{ijt} = k|\mathbf{x}\} = \frac{\mathbf{e}^{\beta_{\mathbf{k}}'\mathbf{x}}}{\mathbf{1} + \sum_{\mathbf{n}=\mathbf{1}}^{\mathbf{3}} \mathbf{e}^{\beta_{\mathbf{n}}'\mathbf{x}}} \tag{114}$$

4.5.3.1 Conditional Logit Model

It can reasonably be argued that the choice set of the multinomial framework is overextended, and that one need only consider a binomial choice set for a relevant analysis. A binomial conditional logit model is used, and allows for better control over the fixed effects as discussed in section (4.5.1.1). There are potentially three ways in which one can consider the 2nd stage interpretation of the donor search model. Given the 3-choice set (113) one can construct relevant binary choice sets to answer more specific questions. The following discusses why these choice sets might be constructed, and how the coding of *giveagain* must be adjusted.

One may reasonably infer that if a donor decides to the make a subsequent contribution via GlobalGiving, regardless of whether it is to a new project or the same project, then this should be taken as evidence of satisfaction with his previous donation. Consequently, no distinction need be made between the choice of give again to the same project, or give again to a different project. This reasoning effectively collapses choice set (113) into set (115).

$$\begin{aligned} k_1 \in \{0 &= \text{do not give again at all,} \\ 1 &= \text{give again to a GlobalGiving project} \end{aligned} \tag{115}$$

during the period in which the donor was formulating his decision to give again or not. In this sense these variables can be considered, to some extent, as propensity scores, and so while *numprojupdts100* represents the actual number of updates posted during a 100 day time span, it can also be considered as a proxy for a project's likelihood to post updates.

Alternatively it may also be argued that a donor who does not donate to the same project again, alternative actions aside, was not satisfied with his previous experience enough to match with that project, and that this should be the set of analysis. Doing so yields the set defined by (116).

$$
\begin{aligned}
k_2 \in \{0 &= \text{do not give again to same project,} \\
1 &= \text{give again to the same project}
\end{aligned} \tag{116}
$$

Lastly, one may argue that the choice model should be nested, in that a donor first makes a decision about whether or not to give again, and then makes a decision about whether to give to the same project or a different project. Consequently, conditioning on those donors who decided to give again the relevant within market analysis is whether they give to the same project or another project. Choice set (117) captures this view.

$$
\begin{aligned}
k_3 \in \{0 &= \text{give again to different project,} \\
1 &= \text{give again to same project}
\end{aligned} \tag{117}
$$

Regardless of the view taken, assuming identical regressors as in the multinomial example, one can model each of the aforementioned binary choice sets via (118).

$$
\text{Prob}\{giveagain_{ijt} = 1|\mathbf{x}\} = \frac{\mathbf{1}}{\mathbf{1} + \mathbf{e}^{-\beta'\mathbf{x}}} \tag{118}
$$

4.6 Empirical Evidence: Main Results

4.6.1 Part I: Results and Analysis

4.6.1.1 Fixed Effects Panel Regression Results

The results from the fixed effects panel regression shown in table (9), imply that neither of the transparency variables "Days Since Last Update"(*daysfrmlastupdt*) and "Total Project Updates"(*numprojupdts*) have a statistically significant impact on the amount of a donor's gift. In fact, considering specification (10) which includes a full compliment of regressors, including controls for time effects, it can be seen that only two project related attributes, the amount of funds raised by a project as a percentage of the fundraising goal and the project's age, were shown to be significant in adjusting a donor's gift level. While statistically significant it is not clear that either regressor is economically significant in the sense that they make any tangible difference in the level of gifts. The estimated coefficient of the "Project Funding" (*amtofprojfunded*) regressor -0.118 can be interpreted as, controlling for all other factors, a 1% increase in the amount of the project funded will cause an $0.118 decline in the donation amount to a given project. This interpretation creates an implicit range on the economic effect of (-$11.80,$0]. This range is a result of *amtofprojfunded* being bounded between 0% and 100%. Potential reasons for why the coefficient can reasonably be argued to be < 0 are discussed in 4.6.1.3.

Also having a statistically significant effect on a donor's contribution level to a project, the project's age has an associated estimated coefficient of 0.127, which would imply that as a project's age increases by 1 day, then the amount of the expected donation would increase by approximately 13 cents. Considering project's range in age from 1 day to 327 days this would imply a range of [$0.13, $42.51], which would certainly be economically significant within the context of a donation range of $10 to $100. While at the lower end of the spectrum, the range is not very significant, as a project hits the 39 day mark, it begins to mean an increase of approximately $5 in the expected donation amount. It seems rather curious that given all of the available project information that the project's age would have such a significant economic effect on the donation amount when controlling for fixed effects. However, there are several factors which could explain this result. In particular there may be a process of attrition taking place, in which only high quality projects survive beyond a certain point, and lower quality projects are dropped from the available listing such that those left in the set are those projects that receive higher funds because of their quality, but the effect is seen via the project age regressor. Furthermore, if one considers that variables such as the number of previous donors, the amount the of funds raised relative to other projects, and how close the project is to its goal effect a project's ranking and subsequent probability of exposure, it would be reasonable to infer that older projects would receive higher donation amounts. Because of the absence of ranking data, and the GlobalGiving portfolio in each period, it is difficult to explicitly control for these factors.

When controls for time effects are relaxed in specifications(7) and (8), the project's age becomes statistically insignificant. While (10) controls for each month, (7) and (8) attempt to control for the period in which the Myanmar and China disasters occurred. Because the disasters both occurred in May, (8) includes a dummy for donations given within the month of May. Specification (7) attempts to bring an even finer level of granularity to the analysis by replacing the month of May dummy, with a dummy that represents gifts given in a period of 18 days around the disaster from May 6th, 2008 - May 23rd, 2008. Outside the context of other period controls these dummies are significant, but become insignificant in specifications (9) and (10) when all months are controlled for.

In specifications (3) through (10) controls are added for two donor characteristics, *subscribe* and *guestcheckout*. Both of these regressors remain significant throughout, but not in the way one would expect. Donors who opt to subscribe, controlling for all other factors, contribute \$1.54 less on average, than those who opt out of a subscription to the GlobalGiving newsletter. In the same vein, Those donors who create a GlobalGiving profile (i.e. do not use the guest checkout option) contribute \$4.08 less on average, than those who use the guest check out option. A possible explanation for this is that donors who subscribe to the newsletter, and/or create profiles, are more likely to contribute on a sustained basis at regular lower amounts, while those who do not create a profile and/or subscribe to the newsletter are drawn to the site for a specific one time gift, which may on average be higher. Whether or not this is true to any significant extent will become more apparent in section (4.6.2)[16].

While these initial results provide some insights into what variables may or may not be significant in terms of the amount of a donor's gift, it not entirely clear how economically significant they are, given the distribution of GlobalGiving donations as presented in Figure (30). The results for the ordered logit model are considered below, and provided to give more context to the results for the fixed effects regression.

4.6.1.2 Ordered Logit Regression

While the ordered logit output is interpreted in a different way than the fixed effects regression output, the logit results imply much the same thing about the factors that influence the level of a donors gift. Table (10) outlines the results from several ordered logit specifications. The output is expressed in the terms of the odds ratio associated with each variable, which is an expression of the probability of being in the one grouping in comparison to all groupings above it in ordering. For instance, if specification (6) is considered, an increase of 1% in the amount of a project's funding goal completed would dictate that the odds of giving above \$50 is 0.990 times less likely than giving any amount \$50 or less (i.e. the odds of being in the highest grouping compared with all combined lower groupings is 0.990 times less likely). The same thing can be said for a transition between any groupings such that it is also 0.990 times less likely to give more than \$15 when compare with giving less than \$15.

Considering specification (6), which controls for both time and fixed effects, it can

[16] An argument can be made that the *subscribe* regressor is not relevant in this context and only serves to complicate the analysis by subsuming the effects of other relevant variables. Regressions were run excluding this variable, and the estimated coefficients of all other regressors showed little to no difference

Table 9: Fixed Effects Panel Regression Model of the Donation Amount ($)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)[a]
Days Since Last Update	-0.0285**	-0.0228*	-0.0267**	-0.0272**	-0.00715	-0.00874	-0.00412	0.00875	0.00654	0.000878
	(0.0120)	(0.0120)	(0.0121)	(0.0123)	(0.0168)	(0.0175)	(0.0176)	(0.0176)	(0.0181)	(0.0194)
Total Previous Donors		0.00243	0.00334*	0.00321		0.00210	0.00178	0.000283	-0.000469	-0.000537
		(0.00199)	(0.00202)	(0.00208)		(0.00220)	(0.00220)	(0.00220)	(0.00222)	(0.00223)
At Least 1 Update? (0/1)				-0.262						-1.242
				(1.031)						(1.144)
Total Project Updates	-1.314***	-1.069***	-1.184***	-1.158***	-1.227***	-0.901*	-0.612	-0.0765	0.0506	0.0788
	(0.136)	(0.413)	(0.416)	(0.429)	(0.146)	(0.461)	(0.480)	(0.472)	(0.475)	(0.476)
Project Funding (%)		-0.148***	-0.169***	-0.164***		-0.156***	-0.155***	-0.143***	-0.135***	-0.118**
		(0.0388)	(0.0392)	(0.0441)		(0.0402)	(0.0402)	(0.0402)	(0.0433)	(0.0470)
Subscribe? (0/1)			-1.739***	-1.739***	-1.674***	-1.704***	-1.687***	-1.583***	-1.798***	-1.544***
			(0.587)	(0.587)	(0.588)	(0.588)	(0.588)	(0.586)	(0.581)	(0.586)
Guest Checkout? (0/1)			3.717***	3.759***	3.728***	4.086***	3.938***	3.356***		4.076***
			(1.092)	(1.105)	(1.119)	(1.122)	(1.124)	(1.123)		(1.250)
Project Age (Days)					-0.0288**	-0.0210	-0.0217	-0.0119	0.127***	0.127**
					(0.0135)	(0.0147)	(0.0147)	(0.0148)	(0.0489)	(0.0495)
Disaster Window? (0/1)[b]							2.567**			
							(1.191)			
Month of May? (0/1)								9.637***		
								(1.227)		
Constant	43.41***	44.51***	44.97***	45.02***	44.10***	45.21***	43.96***	40.05***	60.53***	60.40***
	(0.425)	(0.540)	(0.587)	(0.625)	(0.497)	(0.610)	(0.839)	(0.895)	(14.92)	(14.93)
Observations	11426	11426	11426	11426	11426	11426	11426	11426	11426	11426
R^2	0.010	0.011	0.013	0.013	0.012	0.013	0.013	0.018	0.022	0.023
Number of Projects	251	251	251	251	251	251	251	251	251	251

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[a]Dummy's for each month (February - December) are used for specifcations (9) and (10), but are suppressed.

[b]This variable is a dummy for the period surroudning the Myanmar Cyclone and Chinese Earthquake. It is subsumed by the May dummy, and adds a level of granularity. The dates for which it is true are: May 6th - May 23rd.

be seen that the days since the last project update, the amount of project funding received relative to its goal, whether or not a donor subscribed to the newsletter, and whether or not they chose to use the guest checkout option can all be considered statistically significant in determining a donor's likelihood of increasing or decreasing his donation amount. The ordered logit results differ from the preceding fixed effects regression in that the days since the last project update is now significant, while a project's age is not.

The days since the last project update imply a counter-intuitive result, in that a 1 day increase in the days since the last update cause it to be more likely, by a magnitude of 1.004 times, that a donor will increase his donation to a higher grouping. The magnitude however is small enough is to not be very significant in practice, and so it is not clear that recency of the last update is effective in moving donor's donation levels.

If one recalls Figure (30) it can be seen that the donation groupings are fairly uniformly distributed across donors. As a consequence the variance in the set is extremely small, making the ability to pick up reasons for variation via the regressors difficult, particular in the presence of other explainers. Taking this into consideration, table (18) in the appendix considers each transparency regressor in isolation, and show significant effects in the total project updates measure, along with the days from the last update, which would suggest that the transparency related variables may indeed have some effect on donor choice, as it regards what level to give at. However, while the results are statistically significant within the context of the model, the propotional odds ratios of 1.003 and 1.031 corresponding to the days since the last update, and total project updates, respectively, are not practically significant as they are both very close to 1.[17]

[17]Further regressions on the ordered logit model were also run using various cutoff points, and further sub-intervals among the gift amount groupings. This was done in order to test the robustness of the results, and to see if the relatively low practical significance might be a result of the way in

Table 10: Proportional Odds Ratios for the Ordered Logit Model to Estimate Selection into Donation Groupings

VARIABLES	(1)[a]	(2)	(3)	(4)	(5)	(6)[b]
Days Since Last Update	0.999	1.000	1.002*	1.004***	1.003**	1.004***
	(0.000909)	(0.000917)	(0.00134)	(0.00135)	(0.00147)	(0.00143)
Total Project Updates	0.926***	0.930***	0.980	1.028		1.050
	(0.00800)	(0.0250)	(0.0307)	(0.0316)		(0.0326)
At Least 1 Update? (0/1)					0.931	
					(0.0705)	
Total Previous Donors		1.000***	1.000	1.000	1.000*	1.000
		(0.000130)	(0.000143)	(0.000143)	(7.32e-05)	(0.000146)
Project Funding (%)		0.984***	0.985***	0.986***	0.990***	0.990***
		(0.00249)	(0.00259)	(0.00259)	(0.00306)	(0.00284)
Disaster Window? (0/1)[c]			1.170**			
			(0.0932)			
Subscribe? (0/1)			0.903**	0.909**	0.917**	0.916**
			(0.0361)	(0.0363)	(0.0367)	(0.0366)
Guest Checkout? (0/1)			1.091	1.035	1.252**	1.249**
			(0.0920)	(0.0875)	(0.121)	(0.121)
Project Age (Days)			0.997***	0.998*	1.002	1.001
			(0.00111)	(0.00111)	(0.00366)	(0.00366)
Month of May? (0/1)				2.042***		
				(0.170)		
Observations	10306	10306	10306	10306	10306	10306
Log likelihood	-13088	-13067	-13058	-13023	-12980	-12979
Chi2	2256	2297	2315	2385	2471	2473
DF	60	62	66	66	76	76

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

[a]Categories defined via:

$$dongroup = \begin{cases} 1 & \text{if Amount Donated} \leq \$15 \\ 2 & \text{if Amount Donated} > \$15 \text{ and} \leq \$25 \\ 3 & \text{if Amount Donated} > \$25 \text{ and} \leq \$50 \\ 4 & \text{if Amount Donated} > \$50 \text{ and} \leq \$100 \end{cases}$$

[b]Dummies for each month (February - December) are used for specifcations (5) and (6), but are suppressed. Additionaly, dummies are included for each project in the set, after project's with a frequency of less the 30 appearnces in the set are excluded to avoid incidental parameter problems.

[c]This variable is a dummy for the period surroudning the Myanmar Cyclone and Chinese Earthquake. It is subsumed by the May dummy, and adds a level of granularity. The dates for which it is true are: May 6th - May 23rd.

4.6.1.3 Impact Philanthropy v. Threshold Giving

As discussed in 4.6.1 the existence of a negative coefficient on the *amtofprojfunded* is slightly curious. Below we consider how this might justified, and why it is appropriate to consider *amtofprojfunded* as a percentage. The evidence is motivated by the economic literature on public goods and philanthropy.

Public goods theory introduces the notion of threshold public goods, which are public goods that will, or can, only be provided once a certain funding threshold is met. For instance, a city planning commission may only begin construction of a public train system once they have received enough money such that they can complete the entire construction. Alternatively they could begin construction in phases, whereby once they receive enough money to build one route they begin construction, only going to each phase once there is enough money. Regardless of the approach taken the good should be considered a threshold good in the sense that only once a certain threshold of funds are procured can a useful public train system be provided to the community. In the first scenario the threshold is the entire cost of the project. In the second scenario the minimum threshold is lower because the thresholds are phase specific, but a threshold funding level must be reached nonetheless.

Because the projects on GlobalGiving each have an associated funding goal it might be assumed that donors view these projects as threshold goods, in that a project does not make an impact on the targeted area until the funding goal is reached. If this is the case then it is not a stretch to imagine that the closer a project gets to its goal the more each donor will contribute on average. For instance, if a donor goes to GlobalGiving intending to give \$10 but encounters a project that he would like to give to that is only \$50 away from being completely funded he may decide to give that \$50 so that the public good can be provided. Even if he does not provide the full

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which the initial model was constructed. All of the other variations yielded either similar results, or less significant results.

$50 he may be encouraged to give $20 instead of $10 so as to make the prospect of the good being provided more likely. Observance of this type of behavior would suggest that donor's act in accordance with the threshold theory, and view the public goods found on the GlobalGiving site in this manner. Alternatively, in the sense that it would elicit the opposite behavior from the donor, is the view that donors are impact philanthropists.

Impact philanthropists, as defined by Duncan [32], are donors who seek to maximize the *impact* of the last dollar of their gift. In contrast to the perspective of one who views the goods as threshold goods, an impact philanthropist views the contribution of each additional dollar as having less impact than the previous dollar. This view is a function of the belief that the good is of a continuous nature, in that unlike a threshold good it can be provided once the first $1 is received, with more of the good being provided as funding allows. In this sense, a donor who goes to GlobalGiving ready to make a $20 donation may give only $10 to a project that he intrinsically likes, but already has a high level of funding relative to its goal.[18] There can indeed be a mix of both types of donors, as their probably are. The question that seeks to be answered here, is what type of donor is observed, on average, in the GlobalGiving set.

Not knowing what type of donor exists *a priori*, the coefficient on the *amtofprojfunded* regressor can offer some insight into this question. A coefficient < 0 would suggest that donors, on average are impact giver's, and view the projects provided on GlobalGiving as continuous public goods. A coefficient > 0 would suggest that donors view the goods as threshold, with increases in *amtofprojfunded* leading to increased levels of giving as the project nears its funding goal. Because both types are

[18]One way to think of this is to assume that the donor still gives $20 but distributes it in $10 donations to two closely related projects so that the impact of the $20 is maximized. Alternatively, it may also be the case that this type of donor will choose to give his complete $20 to a substitute good that has less overall funding. However, this deals with a first level choice, and the data set does not contain enough information to make the appropriate inferences.

sensitive to the percentage change in the amount of the project that is funded, it is appropriate that *amtofprojfunded* is expressed as such.

As a consequence the significant coefficient of -0.118 on the *amtofprojfunded* regressor suggests that on average, donor's in the data set view their gift in terms of impact, and are likely to give more, if they perceive their gift as having more impact relative to the gifts of others.

4.6.2 Part II: Results and Analysis

The multinomial logit model is initially considered for discrete choice analysis to estimate the effect of project related information and donor characteristics on the choice set (113). Table (11) presents the relative risk ratios from a multinomial logit estimation, inclusive of controls for time effects, and project specific effects. The risk ratios, which are the exponentiated coefficients of the logit model, are defined relative to the base choice of not to give again (i.e. *giveagain* = 2). The results do not show any significant effect for project related information, other than the project's age, on donor choice in this instance. Whether or not the donor has given previously is shown to be the primary driver in determining the likelihood of a donor returning to GlobalGiving to make a subsequent donation after an initial contribution.

For each additional donation, a donor becomes 4.198 times more likely to give to a different GlobalGiving project in the future than they are to not give again at all, and 3.090 times more likely to give to the same project in the future, than they are to not give again at all. It is not particularly surprising that for each additional gift a donor is more likely to return in the future, as one repeat gift is indicative of some level of satisfaction with the process on the previous iteration, and so each additional gift is evidence of either maintained or increased satisfaction.

The project's age is shown to be significant in the comparison between the choice of giving to a different project and not giving at all, but is not so in considering whether the donor gives again to the same project. In the instance of giving to a different project it is shown that with each additional day that the project has existed the less likely the donor will opt to give again in the future to a GlobalGiving project. Specifically, an increase of 1 day in a project's age will cause the the donor to be 0.964 times more likely to be in the group of individuals which do contribute again via GlobalGiving, which is to say the expectation that they will not give again is increased.

As alluded to earlier, it could be argued that multinomial form is not appropriate for this particular choice modeling, and that the decision should be considered a binary one. Results follow for the binary variants of this multinomial model.

Table (12) presents the discrete choice analysis output for the set defined by (115), such that the results characterize the factors which may influence a donor's decision to give again to the same project that he gave to initially or place his contribution elsewhere (either within or outside GlobalGiving). In this coding of the data the full regressor specification (10), inclusive of controls for the donation period, the project's age is the only significant project attribute. In addition to this attribute, the donor associated characteristic, the donor's number of donations (inclusive) was shown to be significant.

Given a 1 day increase in the age of a project, specification (10) implies a decrease, by a factor of .972, in the odds of a donor choosing to give subsequently to a GlobalGiving affiliated project. That is a project's age at the time of an initial donation is a significant factor in determining whether or not one will donate via GlobalGiving within the subsequent 100 days. The effect of a project's age on the likelihood of repeat giving is counter-balanced, to some extent, by the significance of the variable which measure's how many donations a donor has made previously, inclusive of the current gift. In fact, each subsequent gift by a donor increases the odds of them returning to GlobalGiving within the next 100 days by a magnitude of

Table 11: Relative Risk Ratios for the Multinomial Logit Model to Estimate Selection into Repeat Giving (Don't Return to GlobalGiving (GG) is Reference Group)

VARIABLES*	Choice Equations: Give to Different GG Project	Choice Equations: Give to Same GG Project
Days Since Last Update	1.008	1.000
	(0.00648)	(0.00681)
Total Project Updates	1.175	0.753
	(0.350)	(0.250)
Total Previous Donors	0.990	0.997
	(0.0127)	(0.0190)
Project Funding (%)	1.138	1.503
	(0.116)	(0.544)
New Donors Since	0.989	0.996
	(0.0127)	(0.0189)
New Updates Since	1.118	1.000
	(0.321)	(0.316)
Increase in Funding (%)	1.167	1.487
	(0.117)	(0.535)
Subscribe? (0/1)	1.318*	0.835
	(0.198)	(0.142)
Guest Checkout? (0/1)	1.189	0.786
	(0.810)	(0.606)
Project Age (Days)	0.964***	0.978
	(0.0127)	(0.0139)
Donor's Donation	4.198***	3.090***
	(0.358)	(0.278)
Observations	7292	7292
Log likelihood	-1673	-1673
Chi2	1459	1459
DF	260	260

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

*Dummies for projects and periods are suppressed.

3.56. These two regressors are also shown to be the only one's of significance when coding the choice set as in (116).

Choice set (116) takes the implicit view that if a donor does not give again to the same project, then it is equivalent to not giving to another GlobalGiving project at all. The project's age now has the opposite effect, in that a one day increase in the project's age increases the odds by a magnitude of 1.014 that the donor will give again to the same project within the following 100 days. The number of donation's a donor has made remains significant in the positive direction, but the magnitude of the odds increase is reduced to 1.50.

It is not until the choice set (117), where those donors who did not give again to a GlobalGiving affiliated charity are excluded, does any semblance of significance to project related metrics arise. In this analysis, when not controlling for all periods, two of the project related transparency regressors become significant. Namely, the total project updates, and the number of viewed updates since the initial donation. The total project proportional odds associated with the total project updates is less than 1 in both instances in which it is significant, while the odds increase associated with the post donation updates is greater than 1 in specification (4). The latter observation is in line with expectations and intuition. The meaning of the former is not clear in this context, and perhaps points to some endogeneity issues within the dataset. Table (21) in the appendix considers each transparency related regressor independently, controls for time effects, and finds that none of the transparency regressors remain significant. What does remain significant is the number of donations that a donor has made, and in this case each increasing donation decreases the odds by a factor of approximately 0.7 that a donor will give again to the same project. While this is the opposite effect of the previous two cases there is no overriding justification to argue that it should be one way or the other. When considered in the context of the higher level decision of whether or not the donor gave again at all the meaning was more clear.

Table 12: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (1st Model)

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)[a]
Days Since Last Update	1.000	1.000	1.001				1.000	1.003		1.005
	(0.00327)	(0.00328)	(0.00343)				(0.00352)	(0.00385)		(0.00492)
Total Project Updates	0.984	0.766	0.967				0.701	0.893		0.907
	(0.0257)	(0.157)	(0.0785)				(0.161)	(0.192)		(0.204)
Total Previous Donors			1.000				1.022***	1.003		1.004
			(0.000424)				(0.00849)	(0.00895)		(0.00959)
Project Funding (%)			0.983*				0.865*	0.965		1.066
			(0.00981)				(0.0713)	(0.0783)		(0.0922)
Subscribe? (0/1)			1.151	1.152	1.146	1.141	1.144	1.142	1.087	1.096
			(0.120)	(0.120)	(0.119)	(0.119)	(0.119)	(0.120)	(0.125)	(0.126)
Guest Checkout? (0/1)			1.008	1.014	1.049	0.960	0.983	0.948	1.009	1.028
			(0.498)	(0.501)	(0.519)	(0.481)	(0.485)	(0.477)	(0.516)	(0.526)
Project Age (Days)	1.006**	1.007***	1.007**	1.006***	1.005**	0.989	1.006*	0.989	0.977***	0.972***
	(0.00248)	(0.00266)	(0.00275)	(0.00222)	(0.00227)	(0.00789)	(0.00342)	(0.00836)	(0.00879)	(0.00948)
New Updates Since		0.781		0.987	1.026	1.084	0.738	0.971	1.151*	1.023
		(0.157)		(0.0716)	(0.0756)	(0.0810)	(0.161)	(0.199)	(0.0944)	(0.221)
New Donors Since				1.000	1.000	1.000	1.022***	1.002	0.999	1.003
				(0.000397)	(0.000404)	(0.000407)	(0.00846)	(0.00891)	(0.000437)	(0.00955)
Increase in Funding (%)				1.014	1.018*	1.008	0.881	0.975	1.010	1.075
				(0.00977)	(0.0100)	(0.0103)	(0.0715)	(0.0776)	(0.0111)	(0.0908)
Month of May? (0/1)					0.625***					
					(0.112)					
Donor's Donation									3.542***	3.560***
									(0.268)	(0.271)
Observations	7088	7088	7088	7088	7088	7088	7088	7088	7088	7088

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]Dummy's for each month (February - September) are used for specifcations (6), (8), (9), and (10), but are suppressed.
[b]$k_1 \in \{0 = \text{do not give again at all}, 1 = \text{give again to a GlobalGiving project}\}$

Table 13: Proportional Odds Ratios for the Conditional Logit Model of the “Give Again” Choice (2nd Model)

VARIABLES [a]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days Since Last Update	0.997	0.997	0.994		0.995	0.994	0.995
	(0.00569)	(0.00568)	(0.00594)		(0.00603)	(0.00597)	(0.00603)
Total Project Updates	0.907***	0.774	0.764**		0.597	0.610	0.638
	(0.0330)	(0.243)	(0.0990)		(0.219)	(0.218)	(0.227)
Total Previous Donors			1.001		1.031*	1.032**	1.027
			(0.000737)		(0.0164)	(0.0164)	(0.0170)
Project Funding (%)			0.998		0.676	0.712	0.882
			(0.0180)		(0.205)	(0.214)	(0.277)
New Donors Since				1.000	1.030*	1.031*	1.026
				(0.000696)	(0.0164)	(0.0164)	(0.0169)
New Updates Since		0.854		1.193	0.743	0.835	0.862
		(0.265)		(0.136)	(0.261)	(0.286)	(0.294)
Increase in Funding (%)				0.999	0.676	0.714	0.886
				(0.0178)	(0.203)	(0.214)	(0.277)
Subscribe? (0/1)			0.711**	0.713**	0.717**	0.702**	0.721*
			(0.118)	(0.118)	(0.119)	(0.117)	(0.121)
Guest Checkout? (0/1)			0.717	0.711	0.727	0.736	0.805
			(0.545)	(0.543)	(0.551)	(0.557)	(0.599)
Disaster Window? (0/1) [b]					1.583*		
					(0.417)		
Project Age (Days)	1.020***	1.021***	1.024***	1.020***	1.024***	1.021***	1.014**
	(0.00427)	(0.00435)	(0.00499)	(0.00395)	(0.00664)	(0.00672)	(0.00682)
Month of May? (0/1)						0.721	0.683
						(0.212)	(0.200)
Donor’s Donation							1.500***
							(0.0943)
Observations	6630	6630	6630	6630	6630	6630	6630

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] $k_2 \in \{0 = \text{do not give again to same project}, 1 = \text{give again to the same project}\}$

[b] This variable is a dummy for the period surroudning the Myanmar Cyclone and Chinese Earthquake. It is subsumed by the May dummy, and adds a level of granularity. The dates for which it is true are: May 6th - May 23rd.

Tables (14) and (15) offer some summary statistics of the populations, as represented by their groupings. Table (14) offers an overview of the type of projects, by theme, that receive the donors initial gift for each of the distinct groupings that began this section. The table does not reveal any overt difference between the groups with respect to the types of project they initially give to, other than of those who gave again to the same project a larger percentage of their initial overall contribution went to gender than the other two groups. Table (15) provides more instructive statistics for the two groups of donors who do make repeat contributions. In particular there are significant differences in the means of each population across three categories. The days between gifts, and the amount of the initial donation were both lower for those who gave again to the same project. Most relevant to the preceding analysis the donor who gave again to the same project was able to view, on average, 2.88 updates from their initial project, whereas those who gave to a different project viewed 2.23 updates from the time of their initial gift to the time of their subsequent gift. This occurs even in spite of the fact that donors who give to different projects take longer to do so, which would in effect allow them more time to receive potential updates.

Because of a focus on the subset of donors who do give again one is not longer restricted to dropping donors from the last 100 days of the data set. Table (22) in the appendix considers how the inclusion of the previously dropped observations alters the conditional logit analysis if at all. Almost doubling the number of observations, some slight changes are noted in the significance of the regressors. In particular, the project's initial level of funding, and subsequent post donation level of funding are shown to be significant at 90% in the first three specification, while in the fifth specification whether or not a project was updated in the interval since the donation is shown to be significant at 95%, with the odds of giving to the same project again increasing by a magnitude of 2.347. This is quite a significant result, and hints towards the value of just one update among the set of donors who have already decided to give again.

Table 14: The Initial Donation Project Theme of Donors by whether they "Give Again"

Project Theme	Gave to Different Project	Gave to Same Project	Didn't Give Again	Total
Children	12	0	14	26
Climate	4	3	8	15
Disaster	135	100	4,483	4,718
Econ. Dev	13	11	157	181
Education	22	70	256	348
Environment	3	1	82	86
Finance	1	0	1	2
Gender	23	51	580	654
Health	81	21	1,086	1,188
Hum. Rights	13	3	30	46
Sports	5	1	15	21
Tech	0	0	7	7
Total	312	261	6,719	7,292

It was speculated in section 4.6.1.1 that one might be able to explain the lower level of giving associated with donor's who subscribe to the newsletter by showing that they were more likely to give on a sustained basis, and consequently, give more over the long run. However, the results here do not support this hypothesis as the *subscribe* variable is not shown to be significant in the three cases.

It is also worth considering the effect of disaster related giving on the observed results. As mentioned before, disaster related giving stemming from the Myanmar Cyclone and Chinese Earthquake account for approximately 28% of observed donations. There is an arugment to be made that these projects should not be included in the analyzed data set, as giving to them is driven by outside influences to a much larger extent than other projects on the site.[19] Furthermore, giving to disaster related

[19]The argument can be made that because these events recieved a high level of media exposure in the general population, that the giving to these events are influenced by many more unobservables than projects which are of a more sustained variety on the GlobalGiving site.

Table 15: Summary of statistics for donors who give again to GlobalGiving, either to a new project or to same project.

Give Again?	Days Btw.Gifts	Initial Donation($)	Age(Days)	Updates
New Project	29.84***	84.07**	31.63	2.23**
	-26.49	-153.73	-39.51	-3.37
	[26.89;32.79]	[66.95;101.20]	[27.23;36.03]	[1.85;2.60]
Same Project	15.16***	57.11**	33.75	2.88**
	-14.12	-110.63	-39.59	-4.42
	[13.44;16.88]	[43.63;70.60]	[28.93;38.58]	[2.34;3.42]
Total	23.15	71.79	32.6	2.53
	-22.93	-136.36	-39.52	-3.89
	[21.57;24.73]	[62.41;81.18]	[29.88;35.32]	[2.26;2.79]

Standard deviations in parentheses
95% Confidence intervals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

projects are traditionally viewed as one-off occurences, in which donors give at the time of the event, but do not neccesarily sustain a relationship with the recipient organization or disaster. As such, it is possible the coding of whether or not an individual gives again to the same project or not is skewed by the presence of disaster related data. Consequently, disaster related projects were removed from the set, and the conditonal logit regressions of Tables (19), (20), and (21) were reproducded for the altered set, and are also found in the appendix. The results for both the 2nd and 3rd models, tables (24) and (25) respectively, do not drastically differ from the results with inclusion, as none of the regressors of interest are shown to be significant at a 95% level. However, the 1st model (Table (23)), in which the donor's choice between not giving again at all, or giving again to a GlobalGiving project is considered, shows both statisical, and practical significance for the post donation project update boolean, with an odds ratio of 2.851 at a 99% significance level. With the interpretation that the odds of giving again increase by a factor of 2.851 if a donor recieves an update after his inital donation. In this context, this results suggest that transparency matters to the donor. However, again, we do not see that it is statistically significant in drawing a donor back to a particular project over another.

Table 16: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (3rd Model)

VARIABLES[a]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days Since Last Update	1.000	1.000	0.994		0.998	0.997	0.997
	(0.00788)	(0.00794)	(0.00809)		(0.00850)	(0.00847)	(0.00881)
Total Project Updates	0.865***	1.079	0.612***		0.698	0.701	0.693
	(0.0465)	(0.491)	(0.110)		(0.352)	(0.355)	(0.357)
Total Previous Donors			1.001		1.030	1.028	1.035
			(0.000987)		(0.0221)	(0.0222)	(0.0219)
Project Funding (%)			1.033		0.988	1.077	0.879
			(0.0242)		(0.389)	(0.426)	(0.341)
New Donors Since				0.999	1.029	1.028	1.034
				(0.000925)	(0.0220)	(0.0221)	(0.0218)
New Updates Since		1.245		1.544***	1.096	1.162	1.113
		(0.560)		(0.251)	(0.526)	(0.565)	(0.549)
Increas in Funding (%)				0.968	0.948	1.039	0.849
				(0.0224)	(0.370)	(0.408)	(0.326)
Subscribe? (0/1)			0.758	0.749	0.811	0.788	0.864
			(0.179)	(0.176)	(0.194)	(0.189)	(0.212)
Guest Checkout? (0/1)			0.489	0.462	0.478	0.472	0.425
			(0.502)	(0.474)	(0.491)	(0.486)	(0.438)
Disaster Window? (0/1)[b]					1.950		
					(0.814)		
Project Age (Days)	1.010*	1.010*	1.012*	1.008*	1.006	1.004	1.009
	(0.00553)	(0.00566)	(0.00650)	(0.00503)	(0.00837)	(0.00857)	(0.00884)
Month of May? (0/1)						1.080	1.232
						(0.484)	(0.573)
Donor's Donation							0.784***
							(0.0593)
Observations	469	469	469	469	469	469	469

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] $k_3 \in \{0 = \text{give again to different project}, 1 = \text{give again to same project}\}$

[b] This variable is a dummy for the period surroudning the Myanmar Cyclone and Chinese Earthquake. It is subsumed by the May dummy, and adds a level of granularity. The dates for which it is true are: May 6th - May 23rd.

4.7 Validity Threats

As with most observational data, problems arise when one attempts to establish causal relationships from the provided data set. In contrast to data collected through experiment, observational data requires that the researcher attempt to control for the effect of outside influences on the relationship of interest at the time of analysis, as opposed to at the time of collection [81]. The GlobalGiving data set is not without exception, and some of the issues with the data, particularly as it relates to both internal and external validity are explored below.

There is an initial question of external validity as it concerns the dataset, and the derived results. Ideally, the data set would allow one to make conjectures about the effect of transparency related variables on the giving behavior of the overall population. However, it is not clear that the composition of the data set would allow one to make such a conclusion. The donors who have opted to give donations via GlobalGiving have self selected into the grouping, and as consequence the set consists of donors, who at least to some extent, care about the ideas of transparency and impact in charitable giving. It is highly unlikely that the population contained in the data set is representative of the population at large, and this particular data set does not offer a way in which to test that notion. In general this is not an issue as it concerns the analysis, but it does constrain the conclusions one can make from the analysis. As a result the conclusions are sub-population specific, and not generalizable to the population at large.

While self-selection limits the conclusions that can be made via the set, there are other issues which threaten the internal validity of the analysis, not the least of which are omitted variables which are not found in the data set. With regard to GlobalGiving, and the empirical focus on the question of transparency, project rankings, information placement, and giving amount anchors are all important variables that are not included in the given set. However, the inclusion of the aforementioned variables is not necessarily a panacea for threats to validity.

A project's ranking, as discussed in the introductory section, is determined by GlobalGiving, and comprised of four primary components. The ranking is important, as it drives project exposure which, as the donor search model shows, drives the number of donors that a project will receive. As a consequence, without having the the project's ranking readily accessible it is difficult to distinguish exposure effects on the gift amount and likelihood of return, from the effects of transparency, as the transparency variables are in part drivers of the ranking. The absence of the ranking variable is more pronounced in its effect on the level of the gift than on the donor's likelihood of giving to a project again. Analysis of a donor's likelihood of giving again is largely unaffected as the project is already known to the donor when the analysis begins. Within the constraints of that framework the explicit ranking of a project, and how it changes on a day to day basis is less important to the donor, as it can be understood through the lens of other closely associated input factors. However, for the giving level it is important to control for how donors view the ranking, or a project's placement in the search cue, as a signal of quality. If the ranking is high, a donor may be inclined to give more to that project. While it would be beneficial to have the explicit day to day ranking, the inclusion of several of the inputs in the dataset help to mitigate this problem

It should also be noted that even if the ranking measure were present within the set, validity issues would still persist, particularly as it relates to reverse causality. If one assumes, as the donor search model does, that exposure for a project increases the amount of donations seen by that project then it is not clear that one could make a clean inference as it regards the effect of ranking on the number of donors and vice versa. If ranking increases exposure then the number of donors and amount of donations would be expected to increase. However, because ranking is driven by these components, it can just as easily be stated that increases in the number of donors and amount of donations will cause the ranking to increase. As a consequence the effect of one variable on the other would be hard to distinguish without the appropriate instrument. Because the number and timing of project updates is not explicitly driven by the ranking it does not fall into the aforementioned cycle. However, there are concerns about endogeneity of the update related variables, and whether or not expectations about the return on updates causes underperforming projects to provide more updates, thus biasing the effect on behavior results of updates.[20]

Of even more concern than a project's ranking is the placement of project information within the project page. While all of the project related variables used for analysis were readily available to the donors it is not clear how much of the information the donor viewed. Each piece of information is placed on the page with some pieces receiving more prominent placement than others. For instance, when one visits a project page it is easy to see the amount of money raised, and the number of donors who have contributed thus far, with the amount of funding requested following shortly thereafter. While the days since the most recent update is available, along with all previous updates, this information is not as readily available. As a consequence it is not entirely clear which pieces of information are being viewed. Seen in the analysis thus far, with the exception of table (22), transparency related variables were shown not to have a significant effect on either the level of the gift nor on the decision to return and give again. This may well have to do with placement of this information, as it occurs fairly far down on a project's page. While one may argue that if a donor is truly concerned about these transparency proxies then they will search for them on the page regardless, it would serve the analysis better to have had randomization over page placement, for relevant information.

Another issue posed by how GlobalGiving controls its site is the provision for coherent arbitrariness, or anchoring of the gift amount. It is has been well documented

[20]Chapter 2 speaks to this adverse signaling behavior as a possibility.

that in contributing to public goods donors are often times unaware of their value for the good, while maintaining coherent preferences over goods [8]. As such, a donor can be coaxed to give a certain amount to a project by setting the baseline at that amount. GlobalGiving does this explicitly (perhaps as a side effect) as it offers each potential project donor a menu of options as to what they can contribute toward, and how much a particular impact level will cost. However, these menus vary across projects, and so it is perhaps not fair to compare giving levels across projects without controlling for these menu options. This problem is remedied, to some extent, through the use of fixed effects regression and logit models.

One of the primary concerns in the discrete choice analysis portion is the absence of data on the GlobalGiving project portfolio. The data set does not contain information on all available projects on the GlobalGiving website for a particular day, which would allow for a more thorough analysis of how donors choose between projects. The absence of this data causes a limitation in the type of analysis that can be done, and as discussed earlier it does not allow for one to consider the decision at the fist stage of the donor search model. in particular it does not allow one to fully characterize the discrete choice set. As a consequence the logit models were derived with a focus placed on the attributes of the initial project, and how those attributes contribute toward defining whether or not a donor returned to his a her project. To more fully address the choice issue, more information needs to be known about the attributes of the various alternatives during a given period. As discussed within the context of the framework this required a focus on the second stage giving transaction, and while transparency proxies were not shown to be very significant in this stage, it may be the case that they are most important in the first stage.

While the observational data set presents some limitations on the analysis there are still some conclusions that can be made from the prior analysis, which can serve to help define what is understood about donor behavior.

4.8 Conclusions and Future Work

Given some of the issues raised in section 4.7 a question remains as to what the results mean, and how they should be interpreted with respect to the initial hypotheses, H1 and H2. It was assumed that the defined transparency proxies, the days from the last update and the total number of project updates, would have a positive effect on both the the level of the gift, and the likelihood of repeat giving. A cursory reading of the results would lead one to reject both H1 and H2, as these regressors were shown either to be not statistically significant, or were statistically significant but not practically meaningful, with the exception of a few cases. Of notable exception was the impact of the post donation project update variable for the scenarios outlined in tables (22) and (23). However, these results alone, while encouraging evidence of transparency effects, are not robust enough to not reject H1 and H2 when considered in the context of the holistic analysis conducted throughout. These results, however, must be contextualized within the framework of the population of study.

As discussed previously the results suffer from external validity threats, in that the population under consideration is a specific subset of the population that has self-selected into using the GlobalGiving website, presumably because of its promise of transparency, and mechanisms to monitor impact. One might argue, that as a consequence, if transparency was truly important in giving it would manifest itself in this group more than any other, as donors in the this group have self identified as being transparency conscious. The larger point, however, may be that transparency matters, but only to the point that it allows one to freely give along the dimensions of project preference. In this sense, the donor's view of GlobalGiving as a trustworthy brand provides a baseline beyond which transparency related output does not effect donor behavior in a significant way.

Both GlobalGiving and the donor search model begin with the premise that there is a significant subset of the population that wants to give charitably, for a multitude of reasons, and will do so in greater volume and amounts if transparency is increased. While this analysis lacks the power to make that conclusion definitively, the continued existence, growth and popularity of GlobalGiving, and comparable charitable marketplaces can be offered as evidence in support of that notion.[21] As such, this analysis should not be taken as transparency does not matter in giving, but that it matters to the point that it allows one to feel comfortable about the impact of their contribution. The contrarian viewpoint, that donor's don't care about transparency in the sense that it increases their internalization of the public portion of the gift, but in fact only care about the appearance of transparency in so far as it allows them to enhance their associated *warm-glow* cannot be ruled out. This could in fact be offered as one explanation as to why it does not appear that GlobalGiving donors consider transparency related variables as drivers in their decision making beyond selection into the site. In either case the promise of transparency and tangible impact does seem to play a role in attracting donors to GlobalGiving's site, which might lead one to conclude there is an opportunity for growth in the coming years for competitors and GlobalGiving alike, perhaps with an eye toward specialization among project themes or project countries.

Of particular interest to GlobalGiving and other similarly positioned organizations, is how to continually engage a set of donors who have self-identified as altruists who are willing to give, particularly if the answer does not lie in increased transparency beyond a threshold level. While other social information was shown to have some effect on the level of giving, it is perhaps the diversity of interests contained within one individual that might be best leveraged to engage donors in a more proactive way. Recommendations of similar projects to an individual at the time of the initial gift, or at some point thereafter might serve to re-engage those who no longer

[21] From 2004 to 2008 GlobalGiving had a 13.58% increase in contributions from \$508,653 to \$7,418,503.

have concerns about project validity and impact, but are concerned with simply satisfying their thematic preferences.

Future work in this area should focus on testing a more diverse set of the giving population through large scale field experiments. The emergence and popularity of online markets for charitable giving in recent years allow the researcher to have greater reach and flexibility in testing issues of transparency. There were several factors here which prohibit one from making stronger conclusions about transparency's role in giving that could be mitigated in a more controlled environment. In the effort to both maximize the pool of humanitarian funds, and to better utilize those funds, continued research in understanding how the donor responds to organization behavior is imperative.

4.9 Appendix

Table 17: Fixed Effects Panel Regression Model of the Donation Amount ($)

VARIABLES	(1)	(2)	(3)	(4)[a]
Days Since Last Update	0.00803			
	(0.0172)			
Total Previous Donors		-0.000131		
		(0.00113)		
At Least 1 Update? (0/1)			-1.187	
			(1.046)	
Total Project Updates				-0.0380
				(0.239)
Project Funding (%)	-0.140***	-0.138***	-0.123***	-0.137***
	(0.0257)	(0.0430)	(0.0303)	(0.0378)
Guest Checkout? (0/1)	4.517***	4.491***	4.538***	4.492***
	(1.238)	(1.237)	(1.237)	(1.237)
Project's Age (Days)	0.117**	0.121**	0.125***	0.121***
	(0.0483)	(0.0473)	(0.0470)	(0.0471)
Constant	17.69**	59.29***	59.62***	17.67**
	(7.355)	(14.89)	(14.87)	(7.381)
Observations	11426	11426	11426	11426
Number of Projects	251	251	251	251
R^2	0.022	0.022	0.022	0.022

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a] Dummy's for each month (February - December) are used for all specifications, to control for time effects, but are suppressed.

Table 18: Proportional Odds Ratios for the Ordered Logit Model to Estimate Selection into Donation Groupings

VARIABLES	(1)[a]	(2)	(3)	(4)[b]
Days Since Last Update	1.003**			
	(0.00137)			
Total Previous Donors		1.000*		
		(7.31e-05)		
At Least 1 Update? (0/1)			0.877*	
			(0.0619)	
Total Project Updates				1.031**
				(0.0159)
Project Funding (%)	0.993***	0.989***	0.995**	0.989***
	(0.00171)	(0.00281)	(0.00201)	(0.00247)
Guest Checkout? (0/1)	1.270**	1.256**	1.262**	1.254**
	(0.122)	(0.120)	(0.121)	(0.120)
Project Age (days)	1.001	1.004	1.003	1.004
	(0.00359)	(0.00348)	(0.00345)	(0.00346)
Observations	10306	10306	10306	10306
Log likelihood	-12985	-12987	-12987	-12987
Chi2	2460	2457	2457	2458
DF	72	72	72	72

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] Categories defined via:

$$dongroup = \begin{cases} 1 & \text{if Amount Donated} \leq \$15 \\ 2 & \text{if Amount Donated} > \$15 \text{ and} \leq \$25 \\ 3 & \text{if Amount Donated} > \$25 \text{ and} \leq \$50 \\ 4 & \text{if Amount Donated} > \$50 \text{ and} \leq \$100 \end{cases}$$

[b] Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed. Additionally, dummies are included for each project in the set, after project's with a frequency of less the 30 appearnces in the set are excluded to avoid incidental parameter problems.

Table 19: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (1st Model)

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
Days Since Last Update	1.007	1.006			
	(0.00464)	(0.00483)			
Total Project Updates		0.977	0.955		
		(0.210)	(0.205)		
New Updates Since		1.010	1.006		
		(0.213)	(0.212)		
Total Previous Donors				1.003	
				(0.00931)	
New Donors Since				1.003	
				(0.00932)	
At Least 1 Update? (0/1)					0.919
					(0.185)
At Least 1 Update Since?					1.288
					(0.339)
Project Funding (%)	1.100	1.102	1.077	1.049	1.059
	(0.0723)	(0.0747)	(0.0706)	(0.0856)	(0.0691)
Increase in Funding(%)	1.106	1.103	1.076	1.056	1.063
	(0.0717)	(0.0740)	(0.0693)	(0.0841)	(0.0680)
Donor's Donation	3.544***	3.555***	3.551***	3.527***	3.531***
	(0.268)	(0.270)	(0.270)	(0.266)	(0.267)
Guest Checkout? (0/1)	1.028	1.017	1.016	1.033	1.030
	(0.523)	(0.517)	(0.514)	(0.523)	(0.522)
Project's Age (Days)	0.970***	0.970***	0.973***	0.974***	0.975***
	(0.00923)	(0.00924)	(0.00889)	(0.00899)	(0.00898)
Observations	7088	7088	7088	7088	7088

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

[a] Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b] $k_1 \in \{0 = \text{do not give again at all}, 1 = \text{give again to a GlobalGiving project}\}$

Table 20: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (2nd Model)

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
Days Since Last Update	1.003	0.999			
	(0.00618)	(0.00631)			
Total Project Updates		0.809	0.811		
		(0.251)	(0.251)		
New Updates Since		0.984	0.983		
		(0.300)	(0.300)		
Total Previous Donors				0.997	
				(0.0169)	
New Donors Since				0.997	
				(0.0170)	
At Least 1 Update? (0/1)					1.449
					(0.425)
At Least 1 Update Since?					1.491
					(0.563)
Project Funding (%)	1.249	1.275	1.281	1.320	1.156
	(0.256)	(0.268)	(0.268)	(0.424)	(0.248)
Increase in Funding (%)	1.255	1.246	1.251	1.286	1.169
	(0.256)	(0.260)	(0.260)	(0.412)	(0.248)
Donor's Donation	1.495***	1.503***	1.502***	1.500***	1.509***
	(0.0904)	(0.0930)	(0.0927)	(0.0920)	(0.0921)
Guest Checkout? (0/1)	0.824	0.780	0.777	0.805	0.827
	(0.628)	(0.591)	(0.589)	(0.611)	(0.631)
Project Age (Days)	0.991	0.988	0.988	0.987	0.993
	(0.0129)	(0.0129)	(0.0127)	(0.0128)	(0.0128)
Observations	6630	6630	6630	6630	6630

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b]$k_2 \in \{0 = \text{do not give again to same project}, 1 = \text{give again to the same project}\}$

Table 21: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (3rd Model)

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
Days Since Last Update	1.006	0.999			
	(0.00938)	(0.00931)			
Total Project Updates		0.853	0.853		
		(0.440)	(0.440)		
New Updates Since		1.193	1.192		
		(0.614)	(0.613)		
Total Previous Donors				1.022	
				(0.0247)	
New Donors Since				1.023	
				(0.0248)	
At Least 1 Update? (0/1)					1.172
					(0.470)
At Least 1 Update Since?					1.972
					(1.116)
Project Funding (%)	1.509	1.588	1.593	1.125	1.375
	(0.427)	(0.462)	(0.458)	(0.487)	(0.395)
Increase in Funding (%)	1.505	1.511	1.516	1.072	1.375
	(0.424)	(0.436)	(0.433)	(0.460)	(0.392)
Donor's Donation	0.762***	0.782***	0.782***	0.766***	0.766***
	(0.0593)	(0.0586)	(0.0586)	(0.0584)	(0.0599)
Guest Checkout? (0/1)	0.539	0.437	0.436	0.530	0.541
	(0.554)	(0.451)	(0.449)	(0.539)	(0.555)
Project's Age (Days)	1.009	1.003	1.002	1.006	1.014
	(0.0192)	(0.0193)	(0.0184)	(0.0189)	(0.0183)
Observations	469	469	469	469	469

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b]$k_3 \in \{0 =$ give again to different project, $1 =$ give again to same project$\}$

Table 22: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (3rd Model) with Full Donor Inclusion

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
Days Since Last Update	1.008	1.007			
	(0.00509)	(0.00537)			
Total Project Updates		1.170	1.023		
		(0.480)	(0.406)		
New Updates Since		1.612	1.424		
		(0.665)	(0.570)		
Total Previous Donors				1.006	
				(0.0158)	
New Donors Since				1.008	
				(0.0159)	
At Least 1 Update? (0/1)					1.468
					(0.488)
At Least 1 Update Since?					2.347**
					(0.940)
Project Funding (%)	1.416*	1.474*	1.467*	1.354	1.316
	(0.269)	(0.293)	(0.293)	(0.338)	(0.261)
Increase in Funding (%)	1.403*	1.398*	1.391*	1.286	1.311
	(0.264)	(0.275)	(0.275)	(0.319)	(0.257)
Donor's Donation	0.803***	0.811***	0.810***	0.804***	0.804***
	(0.0323)	(0.0315)	(0.0315)	(0.0313)	(0.0322)
Guest Checkout? (0/1)	0.945	0.800	0.810	0.931	0.950
	(0.597)	(0.507)	(0.509)	(0.580)	(0.595)
Project's Age (Days)	0.985	0.979	0.983	0.983	0.991
	(0.0136)	(0.0138)	(0.0136)	(0.0137)	(0.0135)
Observations	818	818	818	818	818

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b]$k_3 \in \{0 = \text{give again to different project}, 1 = \text{give again to same project}\}$

Table 23: Proportional Odds Ratios for the Conditional Logit Model of the “Give Again” Choice (1st Model) with Disaster Related Projects Excluded

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
Days Since Last Update	1.012**	1.013**			
	(0.00538)	(0.00655)			
Total Project Updates		2.033	1.447		
		(0.950)	(0.639)		
New Updates Since		1.907*	1.868		
		(0.746)	(0.741)		
Total Previous Donors				1.017*	
				(0.0104)	
New Donors Since				1.019*	
				(0.0112)	
At Least 1 Update? (0/1)					1.939
					(0.807)
At Least 1 Update Since?					2.851***
					(1.102)
Project Funding (%)	1.091	1.044	0.998	0.946	0.975
	(0.0788)	(0.0808)	(0.0735)	(0.0835)	(0.0702)
Increase in Funding(%)	1.146**	1.101	1.042	0.984	1.031
	(0.0785)	(0.0823)	(0.0718)	(0.0841)	(0.0684)
Donor’s Donation	3.594***	3.639***	3.563***	3.631***	3.638***
	(0.388)	(0.397)	(0.385)	(0.398)	(0.397)
Guest Checkout? (0/1)	1.909	1.694	1.640	1.671	1.691
	(1.951)	(1.774)	(1.689)	(1.661)	(1.718)
Project’s Age (Days)	0.978*	0.975*	0.984	0.983	0.985
	(0.0118)	(0.0127)	(0.0117)	(0.0115)	(0.0116)
Observations	2379	2379	2379	2379	2379

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b] $k_1 \in \{0 = \text{do not give again at all}, 1 = \text{give again to a GlobalGiving project}\}$

Table 24: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (2nd Model) with Disaster Related Projects Excluded

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
daysfrmlastupdt	1.011	1.012			
	(0.00732)	(0.00997)			
updts		1.643	1.085		
		(1.268)	(0.762)		
diffinupdts100		1.514	1.468		
		(0.865)	(0.857)		
numprevdonors				1.025	
				(0.0222)	
diffindonr100				1.026	
				(0.0233)	
updtbool					1.782
					(1.063)
diffinupdtsbool					2.538*
					(1.350)
threshper	1.137	1.085	1.133	0.697	1.083
	(0.277)	(0.289)	(0.298)	(0.313)	(0.280)
diffinthresh100per	1.162	1.109	1.152	0.707	1.114
	(0.281)	(0.291)	(0.298)	(0.320)	(0.284)
numdonofdonor	1.630***	1.636***	1.630***	1.644***	1.657***
	(0.146)	(0.147)	(0.148)	(0.151)	(0.151)
guestcheckout	1.98e-06	1.75e-06	1.98e-06	6.20e-07	2.02e-06
	(0.00116)	(0.00102)	(0.00117)	(0.000750)	(0.00123)
projagep1	0.990	0.988	0.995	0.996	0.995
	(0.0164)	(0.0174)	(0.0162)	(0.0160)	(0.0162)
Observations	2060	2060	2060	2060	2060

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

[a]Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b]$k_2 \in \{0 = \text{do not give again to same project}, 1 = \text{give again to the same project}\}$

Table 25: Proportional Odds Ratios for the Conditional Logit Model of the "Give Again" Choice (3rd Model) with Disaster Related Projects Excluded

VARIABLES[b]	(1)	(2)	(3)	(4)	(5)[a]
daysfrmlastupdt	1.014	1.010			
	(0.0128)	(0.0184)			
updts		1.273	0.840		
		(1.976)	(1.094)		
diffinupdts100		1.631	1.539		
		(1.868)	(1.714)		
numprevdonors				1.087	
				(0.0662)	
diffindonr100				1.090	
				(0.0702)	
updtbool					1.591
					(1.857)
diffinupdtsbool					3.060
					(3.350)
threshper	1.531	1.452	1.535	0.264	1.298
	(0.621)	(0.689)	(0.703)	(0.360)	(0.570)
diffinthresh100per	1.421	1.348	1.427	0.243	1.206
	(0.571)	(0.636)	(0.648)	(0.337)	(0.527)
numdonofdonor	0.729**	0.729**	0.721**	0.721**	0.734**
	(0.0941)	(0.0963)	(0.0943)	(0.0942)	(0.0966)
guestcheckout	2.09e-07	1.15e-07	1.34e-07	6.64e-07	1.81e-07
	(0.000249)	(0.000167)	(0.000192)	(0.000771)	(0.000265)
projagep1	1.003	1.006	1.015	1.026	1.011
	(0.0278)	(0.0323)	(0.0271)	(0.0287)	(0.0270)
Observations	213	213	213	213	213

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

[a]Dummies for each month (February - December) are used for specifcations to control for time effects in each specification, but are suppressed.
[b]$k_3 \in \{0 = \text{give again to different project}, 1 = \text{give again to same project}\}$

CHAPTER V

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Conclusions and extensions as it regards the specific models and empirical analysis are discussed at the end of each respective chapter. However, if one were to offer an overall conclusion on the thematic work of the dissertation, it would be that information, as it regards organization quality, is significant in determining how donors and organizations conduct themselves within the philanthropic, or charitable, marketplace. While a seemingly obvious result on the surface, the way in which information manifests itself is quite unique with respect to other economic markets. Not only do the dual objectives of the nonprofit alter how information is used, but as was mentioned at the outset the market for charitable goods is quite unique in that donors often times can't experience firsthand the charitable output toward which they contribute. In this respect, information and signals about organization quality and behavior take on heightened importance within the domain of the charitable marketplace.

Chapters 2 and 3, in particular, offer frameworks for how one can begin to think about the effect of information as it regards organization quality and relevance. Chapter 4 offers an empirical analysis that was able to provide some insight into real world donor behavior in a charitable marketplace. This work represents a small piece of a much larger subset of literature and research that has been conducted on why people give, and why organizations comport themselves as they do. In this respect, this dissertation makes a contribution to advancing notions of how information functions within this sector, and provides alternative ways to think about its role. Furthermore, these models have laid the groundwork for future research, particularly as it regards testing and verification of the models both as a whole, and as it regards specific parameters. As was mentioned before, the GlobalGiving observational data set allowed us to take an important first step as it regards verification, but the limits of such a set open the door for experimental techniques. In particular, controlled lab and field experiments, which have been the tools of the experimental economist in the philanthropic sector over the past decade are very amenable to further testing and verification of these models.

Looking toward the future, as social entrepreneurship contains to develop and take center stage within the philanthropic discussion, the way in which people think about giving will continue to expand. Understanding how information can be manipulated and interpreted to maximize impact in organization and institution design will be critical. It is the author's desire that this work will provide more consciousness both from the donor and organization perspective into how behaviors are shaped, with the hope that more efficient use of donor funds that are currently available can be facilitated, and also that the pool of funds from which to draw on can be expanded, so that effective solutions can continue to be implemented through the laudable work of many of these organizations.

REFERENCES

[1] Akerlof, G., "The market for lemons: Qualitative uncertainty and the market mechanism," *The Quarterly Journal of Economics*, vol. 84, no. 3, pp. 488 – 500, 1970.

[2] Alpizar, F., Carlsson, F., and Johansson-Stenman, O., "Does context matter more for hypothetical than for actual contributions? evidence from a natural field experiment," *Experimental Economics*, vol. 11, pp. 299–314, 2008.

[3] Andreoni, J., "Impure altruism and donations to public goods: A theory of warm-glow giving," *The Economic Journal*, vol. 100, no. 401, pp. 467–477, 1990.

[4] Andreoni, J., *Handbook of Giving, Reciprocity and Altruism*, ch. Philanthropy, pp. 1201–1269. 2006.

[5] Andreoni, J., "Leadership giving and charitable fund-raising," *Journal of Public Economic Theory*, vol. 8, no. 1, pp. 1 – 22, 2006.

[6] Andreoni, J. and Scholz, J. K., "An econometric analysis of charitable giving with interdependent preferences," *Economic Inquiry*, vol. 36, no. 3, 1998.

[7] Anheier, H., "Global civil society," tech. rep., The Centre for the Study of Global Governance, 2001.

[8] Ariely, D., Loewenstein, G., and Prelec, D., "coherent arbitrariness: Stable demand curves without stable preferences," *The Quarterly Journal of Economics*, pp. 73–105, February 2003.

[9] Atakan, A. E., "Assortative matching with explicit search costs," *Econometrica*, vol. 74, no. 3, pp. 667–680, 2006.

[10] Barman, E., "With strings attached: Nonprofits and the adoption of donor choice," *Nonprofit and Voluntary Sector Quarterly*, vol. 37, no. 1, pp. 39–56, 2008.

[11] Barnett, M., "Can humanitarianism save itself?," tech. rep., Hubert Humphrey School of Public Affairs, University of Minnesota.

[12] Becker, G. S., "A theory of marriage: Part i," *The Journal of Political Economy*, vol. 81, no. 4, pp. 813–846, 1973.

[13] Bekkers, R. and Wiepking, P., "Generosity and philanthropy - a literature review," 2007.

[14] Bellman, R., *Dynamic Programming.* Princeton University Press, 1957.

[15] Bennett, J., Bertrand, W., Harkin, C., Samarasinghe, S., and Wickramatillake, H., "Coordination of international humanitarian assistance in tsunami-affected countries," tech. rep., Tsunami Evaluation Coalition, July 2006.

[16] Bennett, R. and Kottasz, R., "Emergency fund-raising for disaster relief," *Disaster and Prevention Management*, vol. 8, no. 5, pp. 352 – 359, 2000.

[17] Bilodeau, M. and Slivinski, A., "Rival charities," *The Journal of Public Economics*, vol. 66, pp. 449–467, 1997.

[18] Blackwood, A., Wing, K. T., and Pollak, T. H., "The nonprofit sector in brief: Facts and figures from the nonprofit almanac 2008," tech. rep., The Urban Institute, 2008.

[19] Borton, J., "Recent trends in the international relief system," *Disasters*, vol. 17, no. 3, pp. 187–201, 1993.

[20] Bowman, W., "Should donors care about overhead costs? do they care?," *Nonprofit and Voluntary Sector Quarterly*, vol. 35, pp. 288–310, 2006.

[21] Brown, P. and Minty, J., "Media coverage & charitable giving after the 2004 tsunami," Working Paper 855, William Davidson Institute at The University of Michigan, 2006.

[22] Casataneda, M. A., Garen, J., and Thornton, J., "Competition, contractibility, and the market for donors to nonprofits," *Journal of Law, Economics, & Organization*, vol. 24, no. 1, 2007.

[23] Clinton, B., *Giving: How Each of Us Can Change the World.* New York: Alfred A. Knopf, 2007.

[24] Cooley, A. and Ron, J., "Perverse aid: The new market for foreign assistance."

[25] Cooley, A. and Ron, J., "The ngo scramble: Organizational insecurity and the political economy of transnational action," *International Security*, vol. 27, no. 1, pp. 5–39, 2002.

[26] Cornes, R. and Sandler, T., *The Theory of Externalities, Public Goods, and Club Goods.* Cambridge University Press, 1996.

[27] Crawford, V. and Sobel, J., "Strategic information transmission," *Econometrica*, vol. 50, no. 6, pp. 1431 – 1451, 1982.

[28] Croson, R. and Shang, J., "The impact of downward social information on contribution decisions," *Experimental Economics*, vol. 11, pp. 221–233, 2008.

[29] Crumpler, H. and Grossman, P., "An experimental test of warm glow giving," *Journal of Public Economics*, vol. 92, no. 5-6, pp. 1011 – 1021, 2008.

[30] Darby, M. R. and Karni, E., "Free competition and the optimal amount of fraud," *The Journal of Law and Economics*, vol. 16, pp. 67–88, 1973.

[31] Donini, A. and Niland, N., "Lessons learned: A report on the coordination of humanitarian activities in rwanda," tech. rep., United Nations Department of Humanitarian Affairs (DHA), 1-51 1994.

[32] Duncan, B., "A theory of impact philanthropy," *Journal of Public Economics*, vol. 88, pp. 2159–2180, 2004.

[33] Feigenbaum, S., "Competition and performance in the nonprofit sector: The case of us medical research charities," *The Journal of Industrial Economics*, vol. 35, no. 3, pp. 241–253, 1987.

[34] Frumkin, P. and Kim, M. T., "Strategic positioning and the financing of nonprofit organizations: Is efficiency rewarded in the contributions marketplace?," *Public Administration Review*, vol. 61, no. 3, p. 266, 2001.

[35] Fudenberg, D. and Tirole, J., *Game Theory.* The MIT Press, 1991.

[36] Garman, S., Hampshire, R., and Krishnan, R., "A search theoretic model of person-to-person lending." May 2008.

[37] Ghosh, S. and Van Tassel, E., "A model of mission drift in microfinance institutions." 2008.

[38] Glazer, A. and Konrad, K., "A signaling explanation for private charity," *American Economic Review*, vol. 86, no. 4, pp. 1019 – 1028, 1996.

[39] Greene, W. H., *Econometric Analysis.* Prentice Hall, 5th ed., 2003.

[40] Hall, J., "Too many ways to divide donations?," *The Christian Science Monitor.*

[41] Handy, F., "How we beg: The analysis of direct mail appeals," *Nonprofit and Voluntary Sector Quarterly*, vol. 29, no. 3, pp. 439–454, 2000.

[42] Hansmann, H., "The role of nonprofit enterprise," *The Yale Law Journal*, vol. 89, no. 5, 1980.

[43] Harbaugh, W., "What do donations buy? a model of philanthropy based on prestige and warm glow," *Journal of Public Economics*, vol. 67, pp. 269 – 284, 1998.

[44] Hibbert, S. and Horne, S., "Giving to charity: questioning the donor decision process," *Journal of Consumer Marketing*, vol. 13, no. 2, pp. 4–13, 1996.

[45] Hitsch, G., Hortacsu, A., and Ariely, D., "What makes you click? mate preferences and matching outcomes in online dating." April 2006.

[46] Holtmann, A. G., "A theory of non-profit firms," *Economica*, vol. 50, no. 200, pp. 439–449, 1983.

[47] Hsu, J. L., Liang, G.-Y., and Tien, C.-P., "Social concerns and willingness to support charities," *Social Behavior and Personality*, vol. 33, no. 2, pp. 189–200, 2005.

[48] James, E., "How nonprofits grow: A model," *Journal of Policy Analysis and.*

[49] Jovanovic, B., "Job matching and the theory of turnover," *The Journal of Political Economy*, vol. 87, no. 5, pp. 972–990, 1979.

[50] Karlan, D. and List, J. A., "Does price matter in charitable giving? evidence from a large-scale natural field experiment," *The American Economic Review*, vol. 7, December 2007.

[51] Kottasz, R., "Differences in the donor behavior characteristics of young affluent males and females: Empirical evidence from britain," *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, vol. 15, no. 2, 2004.

[52] Lankford, R. H. and Wyckoff, J. H., "Modeling charitable giving using a box-cox standard tobit model," *The Review of Economics and Statistics*, vol. 73, no. 3, 1991.

[53] Lippman, S. and McCall, J., eds., *Studies in the Economics of Search*, vol. 123 of *Contributions to Economic Analysis.* North-Holland Publishing Company, 1979.

[54] Lipson, M., "Interorganizational networks in peacekeeping and humanitarian relief: An institutional theory perspective," in *Annual Meeting of the American Political Science Association*, (Philadelphia, PA), p. 29, 2003.

[55] List, J. A., "Introduction to field experiments in economics with applications to the economics of charity," *Experimental Economics*, vol. 11, pp. 203–212, 2008.

[56] Ljungqvist, L. and Sargent, T. J., *Recursive Macroeconomic Theory.* Massachusetts Institute of Technology, 2000.

[57] Macrae, J. and Harmer, A., "Humanitarian action and the 'global war on terror': a review of trends and issues," Tech. Rep. 14, Overseas Development Institute: Humanitarian Policy Group, July 2003 2003.

[58] Marinescu, I., "Labor market shocks and marriage duration." October 2008.

[59] Mas-Colell, A., Whinston, M. D., and Green, J. R., *Microeconomic Theory.* Oxford University Press, Inc., 1995.

[60] McCall, J., "Economics of information and job search," *The Quarterly Journal of Economics*, vol. 84, no. 1, pp. 113–126, 1970.

[61] Meijer, M.-M., "The effects of charity reputation on charitable giving," *Corporate Reputation Review*, vol. 12, no. 1, pp. 33–42, 2009.

[62] Milgrom, P. and Roberts, J., "Price and advertising signals of product quality," *The Journal of Political Economy*, vol. 94, no. 4, pp. 796 – 821, 1986.

[63] Minear, L., *The Humanitarian Enterprise: Dilemmas and Discoveries*. Bloomfield, CT: Kumarian Press, Inc., 2002.

[64] Minear, L., Chelliah, U., Crips, J., Mackinlay, J., and Weiss, T. G., "Un coordination of the international humanitarian response to the gulf crisis 1990 - 1992," Tech. Rep. 13, Thomas J. Watson Institute for International Studies, 1992.

[65] Mirrlees, J., "An exploration in the theory of optimum income taxation," *The Review of Economic Studies*, vol. 38, no. 2, pp. 175 – 208, 1971.

[66] Moore, S., Eng, E., and Daniel, M., "International ngos and the role of network centrality in humanitarian aid operations: A case study of coordination during the 2000 mozambique floods," *Disasters*, vol. 27, no. 4, pp. 305–318, 2003.

[67] Moorthy, S. and Srinivasan, K., "Signaling quality with a money-back guarantee: The role of transaction costs," *Marketing Science*, vol. 14, no. 4, 1995.

[68] Natsios, A. S., "Ngos and the un system in complex humanitarian emergencies: conflict or cooperation?," *Third World Quarterly*, vol. 16, no. 3, pp. 405–419, 1995.

[69] Nelson, P., "Information and consumer behavior," *Journal of Political Economy*, vol. 78, no. 2, pp. 311–329, 1970.

[70] Nelson, P., "Information and consumer behavior," *The Journal of Political Economy*, vol. 78, no. 2, pp. 311 – 329, 1970.

[71] Pepall, L., Richards, D., Straub, J., and DeBartolo, M., "Crowding out and competition in the religious marketplace." 2007.

[72] Radley, A. and Kennedy, M., "Charitable giving by individuals: A study of attitudes and practice," *Human Relations*, vol. 48, no. 6, 1995.

[73] Reindorp, N. and Wiles, P., "Humanitarian coordination: Lessons from recent field experience," tech. rep., Overseas Development Institute, June 2001 2001.

[74] Reinhardt, G., "Matching donors and nonprofits: The importance of signaling in funding awards." Working Paper, 2007.

[75] Ribar, D. C. and Wilhelm, M. O., "Altruistic and joy-of-giving motivations in charitable behavior," *Journal of Political Economy*, vol. 110, no. 2, 2002.

[76] Riley, J., "Silver signals: Twenty-five years of screening and signaling," *Journal of Economic Literature*, vol. 39, no. 2, pp. 432–478, 2001.

[77] Romano, R. and Yildirim, H., "Why charities announce donations: A positive perspective," *Journal of Public Economics*, vol. 81, no. 3, pp. 423 – 447, 2001.

[78] Rondeau, D. and List, J. A., "Matching and challenge gifts to charity: evidence from laboratory and natural field experiments," *Experimental Economics*, vol. 11, pp. 253–267, 2008.

[79] Rose-Ackerman, S., "Charitable giving and "excessive" fundraising," *The Quarterly Journal of Economics*, vol. 97, no. 2, pp. 193–212, 1982.

[80] Rose-Ackerman, S., "Altruism, nonprofits, and economic theory," *Journal of Economic Literature*, vol. 34, no. 2, pp. 701 – 728, 1996.

[81] Rosenbaum, P. R., "Observational Study," in *Encyclopedia of Statistics in Behavioral Science* (Everitt, B. S. and Howell, D. C., eds.), pp. 1451–1462, John Wiley & Sons, 2005.

[82] Roth, A. E. and Sotomayor, M. A. O., *Two-Sided Matching: A study in game-theoretic modeling and analysis*. Cambridge University Press, 1992.

[83] Rothschild, M., "Models of market organization with imperfect information: A survey," *Public Administration Review*, vol. 81, no. 6, pp. 1283–1308, 1973.

[84] Sargeant, A., "Charitable giving: Towards a model of donor behaviour," *Journal of Marketing Management*, vol. 15, pp. 215–238, 1999.

[85] Sargeant, A., Ford, J. B., and West, D. C., "Perceptual determinants of nonprofit giving behavior," *Journal of Business Research*, vol. 59, pp. 155–165, 2006.

[86] Sargeant, A., West, D. C., and Ford, J., "The role of perceptions in predicting donor value," *Journal of Marketing Management*, vol. 17, no. 3-4, pp. 407–428, 2001.

[87] Sargeant, A. and Woodliffe, L., "Gift giving: An interdisciplinary review," *International Journal of Nonprofit and Voluntary Sector Marketing*, vol. 12, no. 4, 2007.

[88] Shimer, R. and Smith, L., "Assortative matching and search," *Econometrica*, vol. 68, no. 2, pp. 343–369, 2000.

[89] Simon, A., "Television news and international earthquake relief," *Journal of Communication*, vol. 47, no. 3, 1997.

[90] Smillie, I., "Relief and development: The struggle for synergy," 1998.

[91] Spence, M., "Job market signaling," *The Quarterly Journal of Economics*, vol. 87, no. 3, pp. 355 – 374, 1973.

[92] Steinberg, R., "The revealed objective functions of nonprofit firms," *The RAND Journal of Economics*, vol. 17, no. 4, pp. 508–526, 1986.

[93] Stephenson, Max, J., "Making humanitarian relief networks more effective: Exploring the relationships among coordination, trust and sense making," *Disasters*, vol. 29, no. 4, 2005.

[94] Stephenson, Max, J. and Schnitzer, M., "Interorganizational trust, boundary spanning and humanitarian relief coordination," *Nonprofit Management & Leadership*, vol. 17, no. 2, 2006.

[95] Stigler, G., "The economics of information," *The Journal of Political Economy*, vol. 69, no. 3, pp. 213–225, 1961.

[96] Stockton, N., "Strategic coordination in afghanistan," tech. rep., August 2002 2002.

[97] Tisdell, C. and Wilson, C., "Information, wildlife valuation, conservation: Experiments and policy," *Contemporary Economic Policy*, vol. 24, no. 1, pp. 144 – 159, 2006.

[98] Tuckman, H. P., "Competition, commercialization, and the evolution of nonprofit organizational structures," *Journal of Policy Analysis and Management*, vol. 17, no. 2, pp. 175–194, 1998.

[99] Venable, B. T., Rose, G. M., Bush, V. D., and Gilbert, F., "The role of brand personality in charitable giving: An assessment and validation," *Journal of the Academy of Marketing Science*, vol. 33, no. 3, 2005.

[100] Vesterlund, L., "The informational value of sequential fundraising," *Journal of Public Economics*, vol. 87, pp. 627 – 657, 2003.

[101] Vickrey, W., "Counterspeculation, auctions and competitive sealed tenders," *Journal of Finance*, vol. 16, no. 1, pp. 41 – 50, 1961.

[102] Weisbrod, B. A., ed., *The Voluntary Nonprofit Sector*. Lexington Books, 1977.

[103] Wilde, L. L., *Studies in the Economics of Search*, ch. An Information-Theoretic Approach to Job Quits. Yale University Press, 1987.

[104] Williamson, O. E., "Transaction-cost economics: The governance of contractual relations," *Journal of Law and Economics*, vol. 22, no. 2, pp. 233–261, 1979.

[105] Willitts-King, B. and Harvey, P., "Managing the risks of corruption in humanitarian relief operations," tech. rep., Overseas Development Institute - Humanitarian Policy Group, 2005/3/31 2005.

[106] Wolpert, J. and Reiner, T., "A philanthropy marketplace," *Economic Geography*, vol. 60, no. 3, pp. 197–209, 1984.

[107] Wood, J., "Improving ngo coordination: lessons from the bam earthquake," tech. rep., Humanitarian Practice Network, 2004/15/07 2004.

[108] Yashiv, E., "Labor search and matching in macroeconomics," *European Economic Review*, vol. 51, pp. 1859–195, 2007.

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